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Gopinathan et al.

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[45] **Date of Patent: Oct. 6, 1998**

[54] **FRAUD DETECTION USING PREDICTIVE MODELING**

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[73] Assignee: **HNC Software Inc.**, San Diego, Calif.

[21] Appl. No.: **941,971**

[22] Filed: **Sep. 8, 1992**

[51] **Int. Cl.^{6}** **G06F 157/00**

[52] **U.S. Cl.** **705/1**

[58] **Field of Search** 364/401, 406, 364/408; 395/21, 23; 235/23, 380; 705/35, 1

[56] **References Cited**

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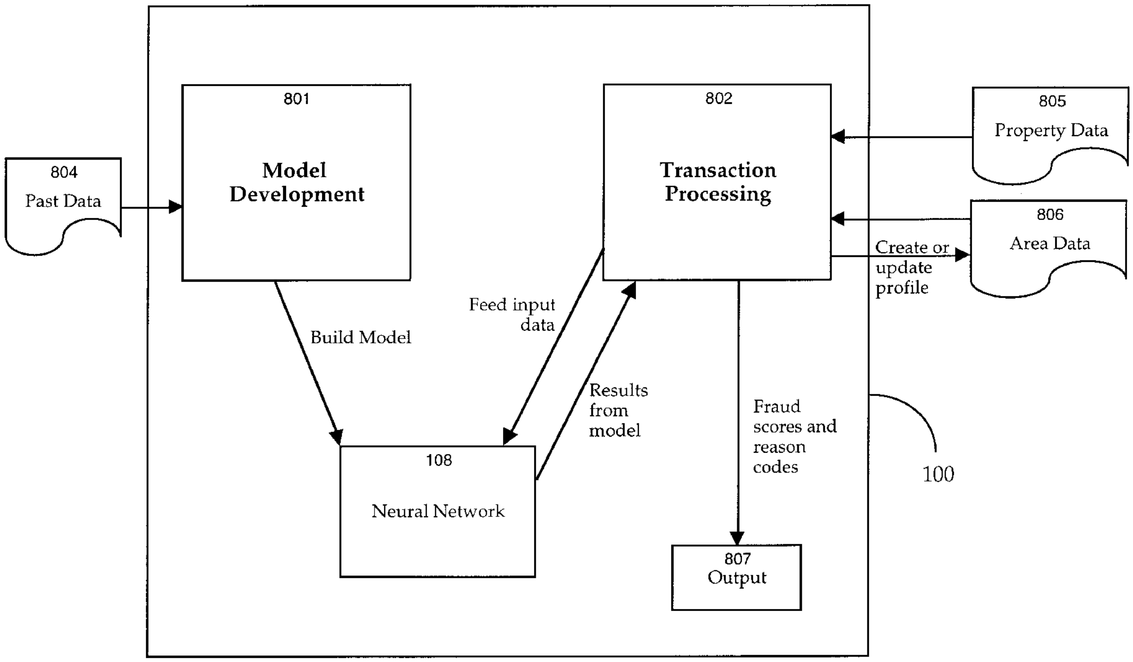
Primary Examiner—Gail O. Hayes
Attorney, Agent, or Firm—Fenwick & West LLP

[57] **ABSTRACT**

An automated system and method detects fraudulent transactions using a predictive model such as a neural network to evaluate individual customer accounts and identify potentially fraudulent transactions based on learned relationships among known variables. The system may also output reason codes indicating relative contributions of various variables to a particular result. The system periodically monitors its performance and redevelops the model when performance drops below a predetermined level.

38 Claims, 21 Drawing Sheets



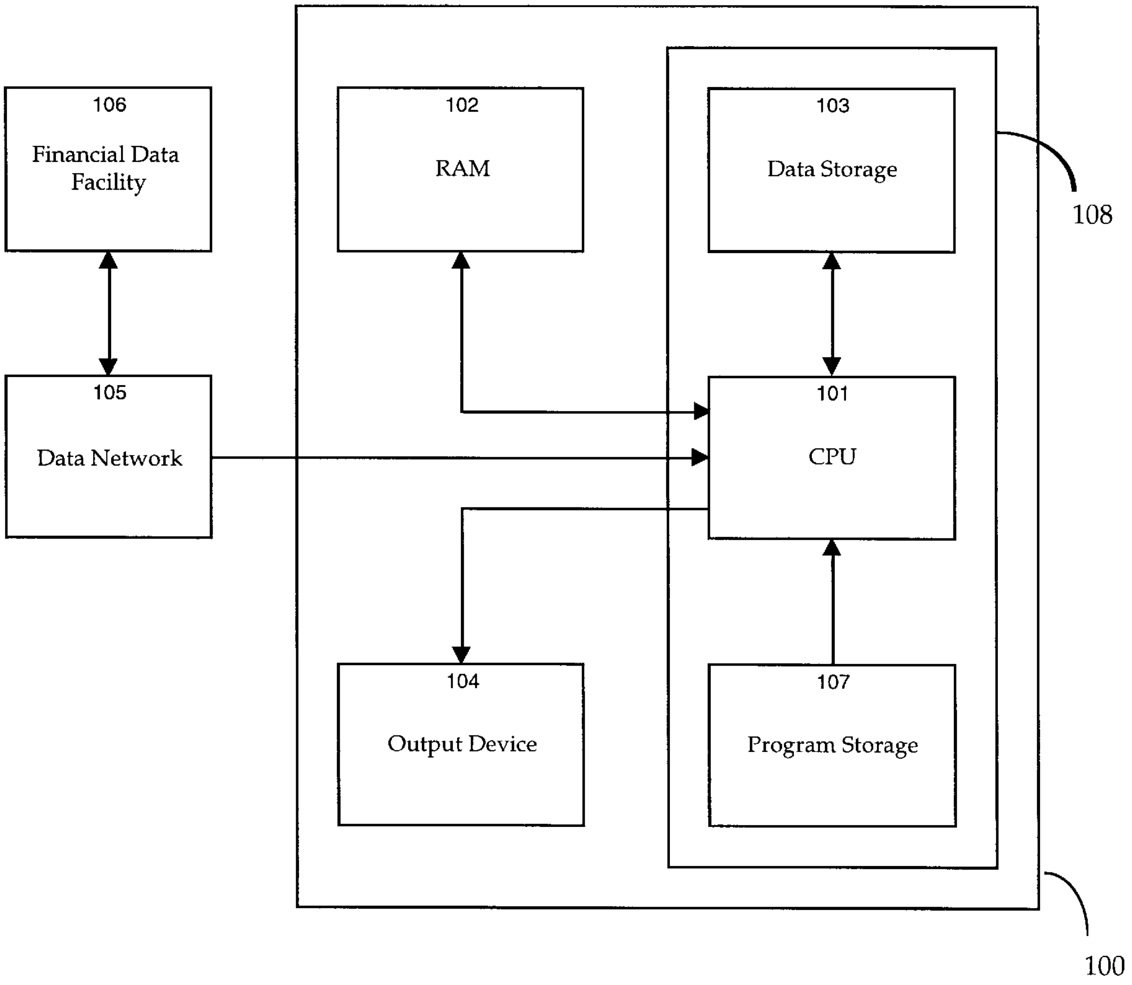
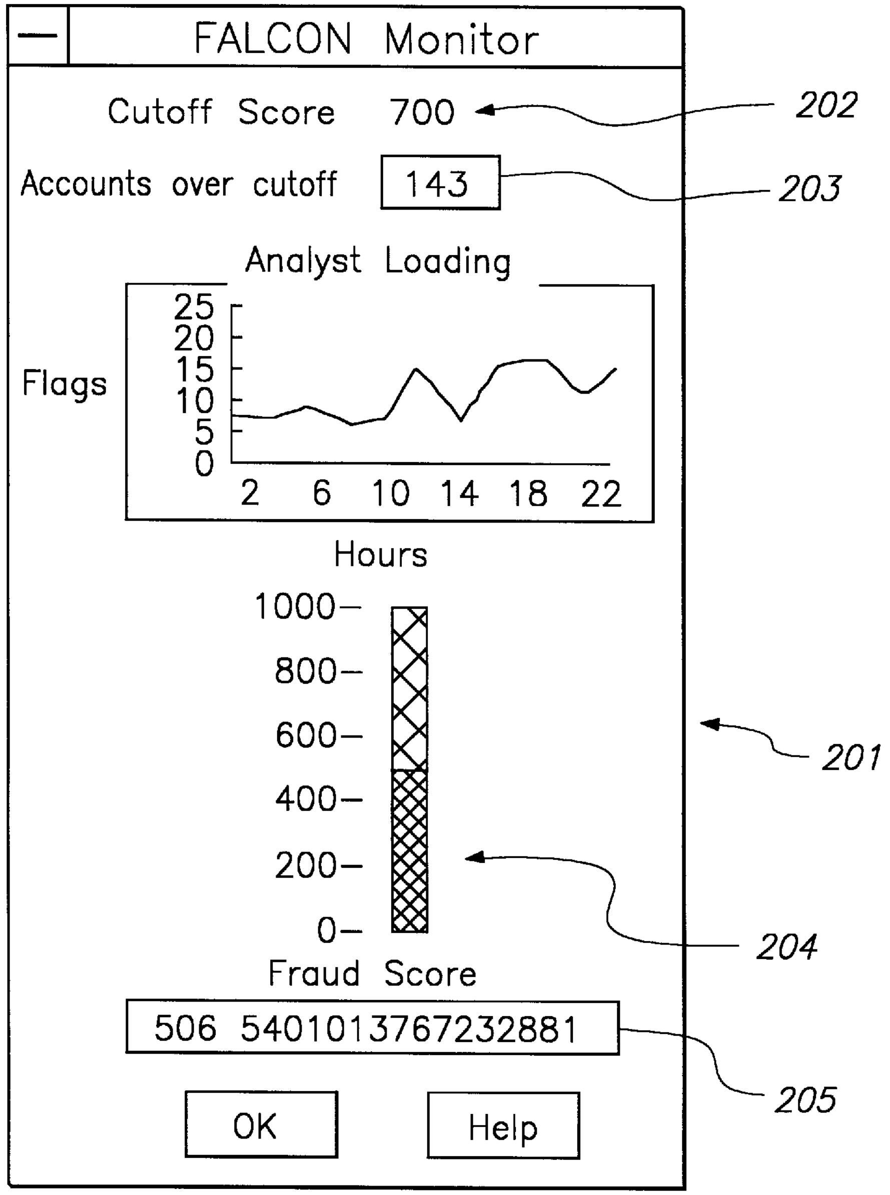

106
Financial Data Facility
105
Data Network
102
RAM
103
Data Storage
108
101
CPU
104
Output Device
107
Program Storage
100

FIGURE 1



FALCON Monitor

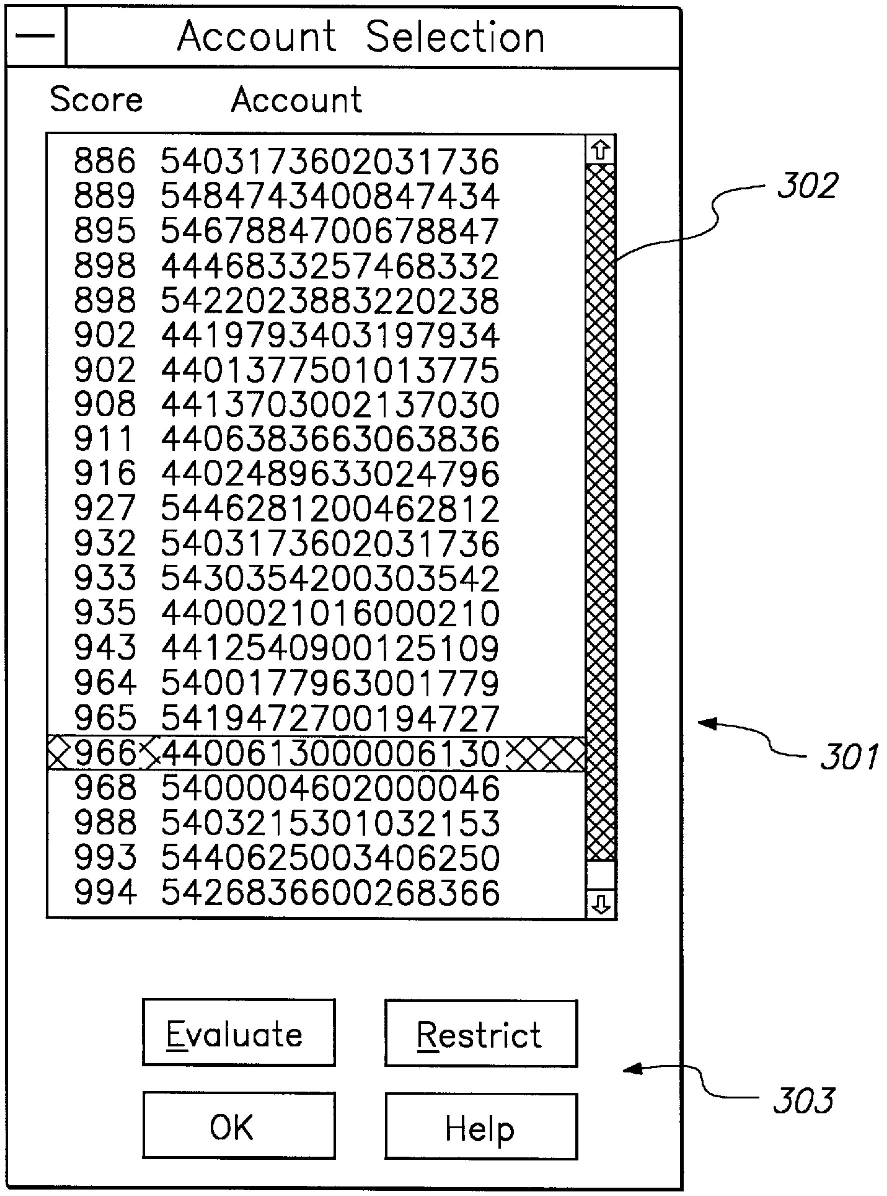
Cutoff Score 700

Accounts over cutoff 143

Fraud Score

506 5401013767232881

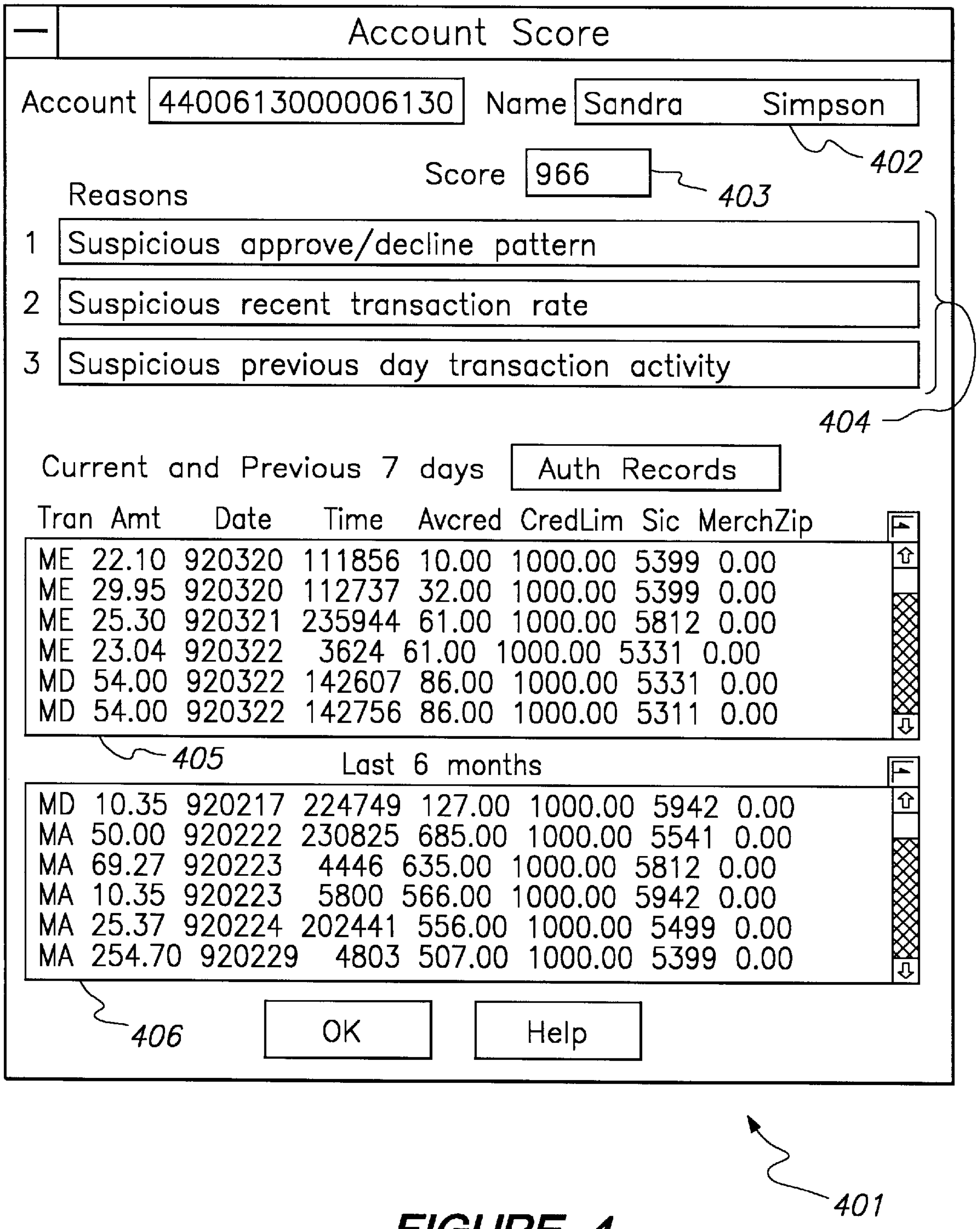
FIGURE 2



Account Selection

Score	Account
886	5403173602031736
889	5484743400847434
895	5467884700678847
898	4446833257468332
898	5422023883220238
902	4419793403197934
902	4401377501013775
908	4413703002137030
911	4406383663063836
916	4402489633024796
927	5446281200462812
932	5403173602031736
933	5430354200303542
935	4400021016000210
943	4412540900125109
964	5400177963001779
965	5419472700194727
966	4400613000006130
968	5400004602000046
988	5403215301032153
993	5440625003406250
994	5426836600268366

FIGURE 3



Account Score

Account 4400613000006130 Name Sandra Simpson

Score 966

Reasons

1 Suspicious approve/decline pattern

2 Suspicious recent transaction rate

3 Suspicious previous day transaction activity

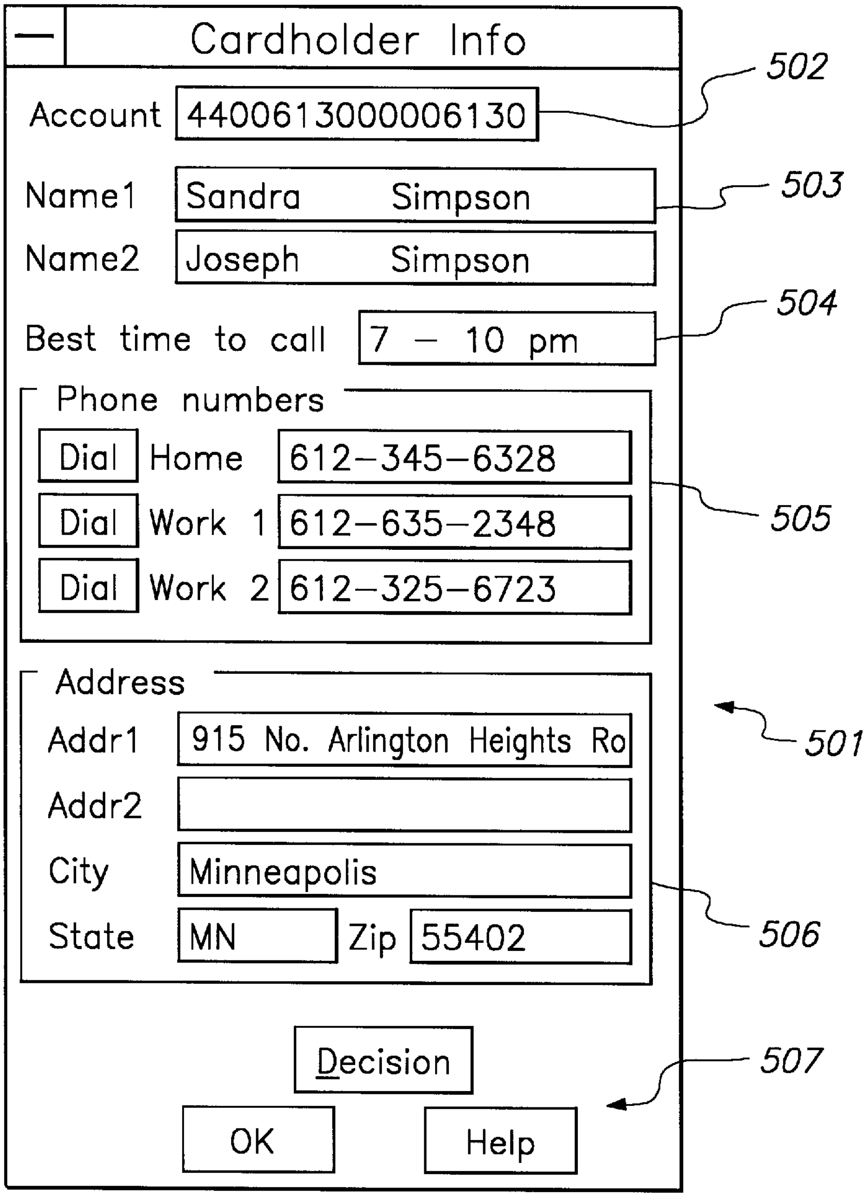
Current and Previous 7 days

Tran	Amt	Date	Time	Avcred	CredLim	Sic	MerchZip
ME	22.10	920320	111856	10.00	1000.00	5399	0.00
ME	29.95	920320	112737	32.00	1000.00	5399	0.00
ME	25.30	920321	235944	61.00	1000.00	5812	0.00
ME	23.04	920322	3624	61.00	1000.00	5331	0.00
MD	54.00	920322	142607	86.00	1000.00	5331	0.00
MD	54.00	920322	142756	86.00	1000.00	5311	0.00

Last 6 months

MD	10.35	920217	224749	127.00	1000.00	5942	0.00
MA	50.00	920222	230825	685.00	1000.00	5541	0.00
MA	69.27	920223	4446	635.00	1000.00	5812	0.00
MA	10.35	920223	5800	566.00	1000.00	5942	0.00
MA	25.37	920224	202441	556.00	1000.00	5499	0.00
MA	254.70	920229	4803	507.00	1000.00	5399	0.00

FIGURE 4



Cardholder Info

Account 4400613000006130

Name1 Sandra Simpson

Name2 Joseph Simpson

Best time to call 7 – 10 pm

Phone numbers

Home 612–345–6328

Work 1 612–635–2348

Work 2 612–325–6723

Address

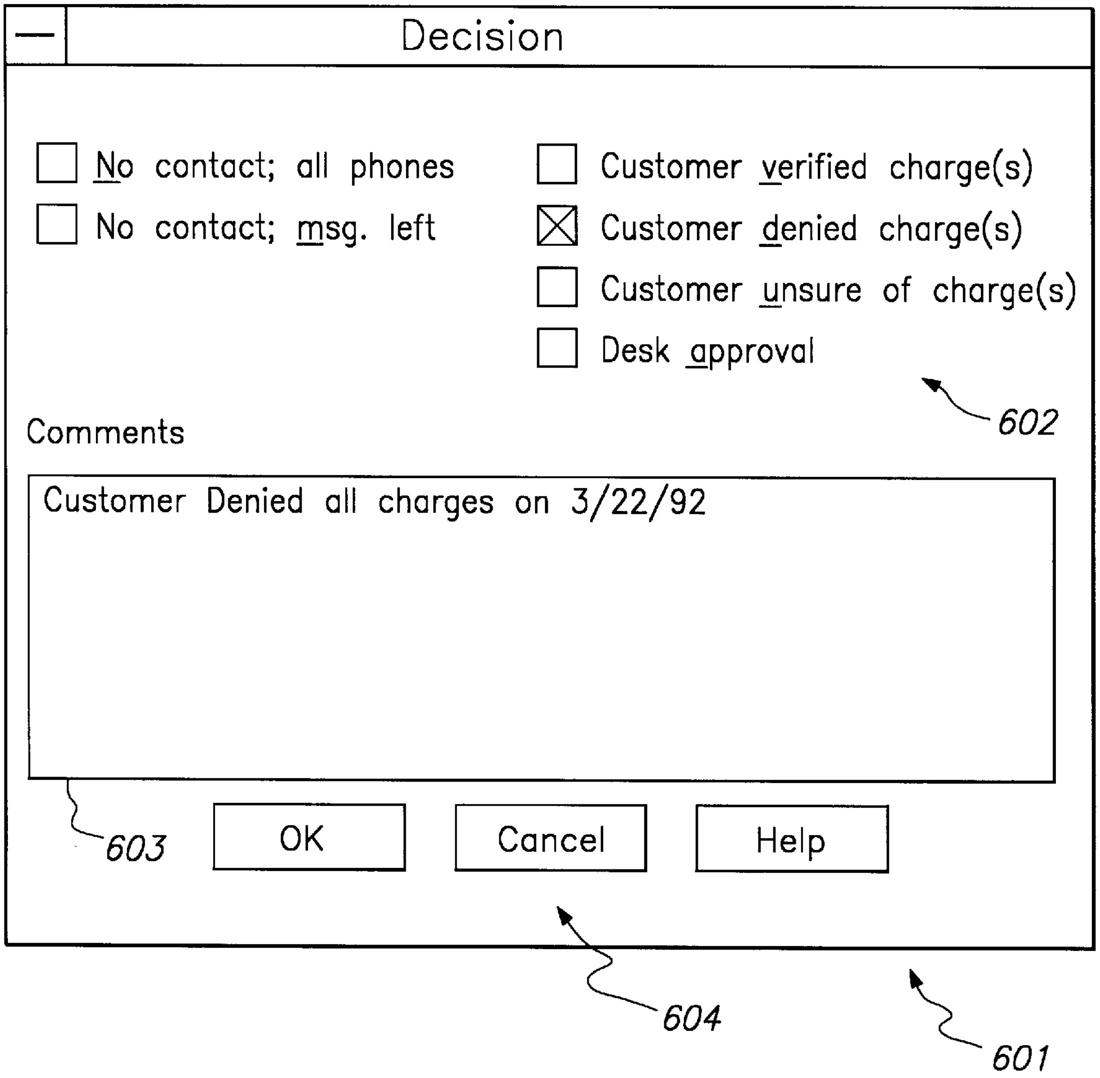
Addr1 915 No. Arlington Heights Ro

Addr2

City Minneapolis

State MN Zip 55402

FIGURE 5



Decision

□ No contact; all phones

□ No contact; msg. left

□ Customer verified charge(s)

☒ Customer denied charge(s)

□ Customer unsure of charge(s)

□ Desk approval

Comments

Customer Denied all charges on 3/22/92

FIGURE 6

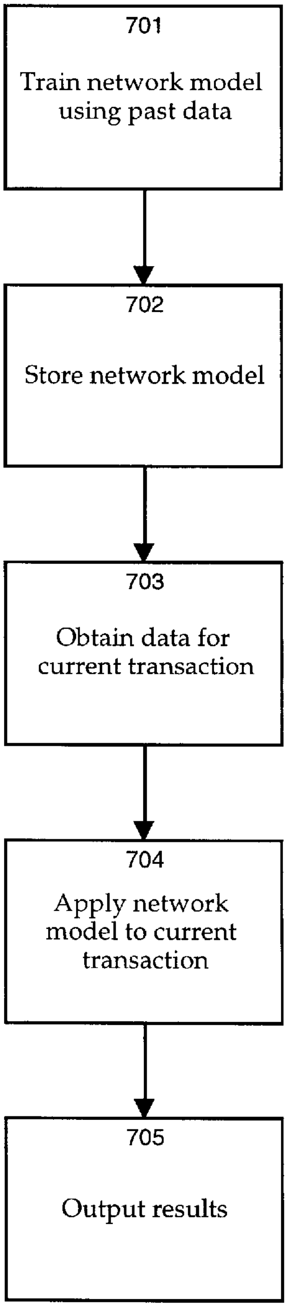

701
Train network model using past data
702
Store network model
703
Obtain data for current transaction
704
Apply network model to current transaction
705
Output results

FIGURE 7

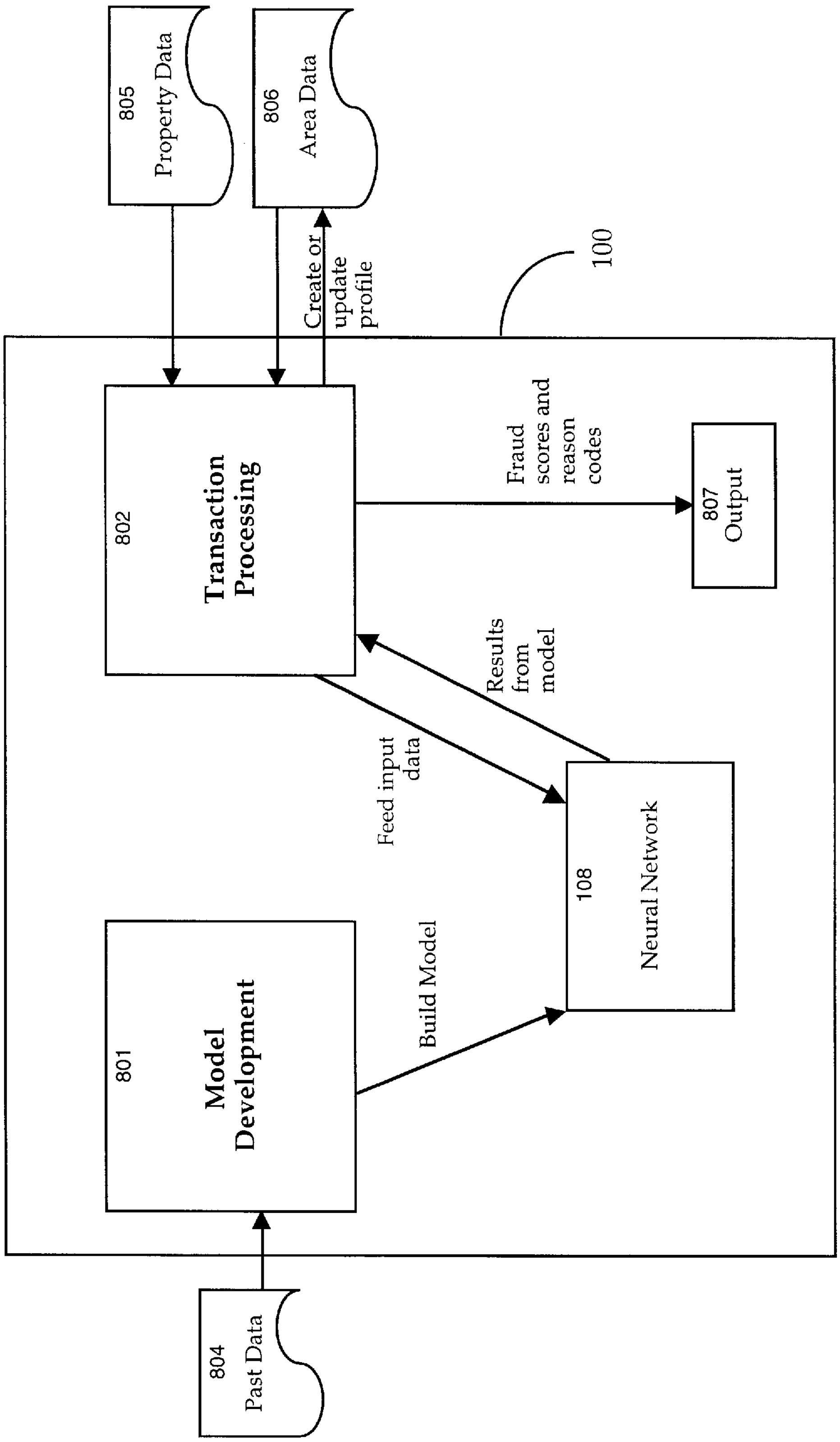

805
Property Data
806
Area Data
Create or update profile
100
802
Transaction Processing
Fraud scores and reason codes
807
Output
Results from model
Feed input data
108
Neural Network
801
Model Development
Build Model
804
Past Data

FIGURE 8

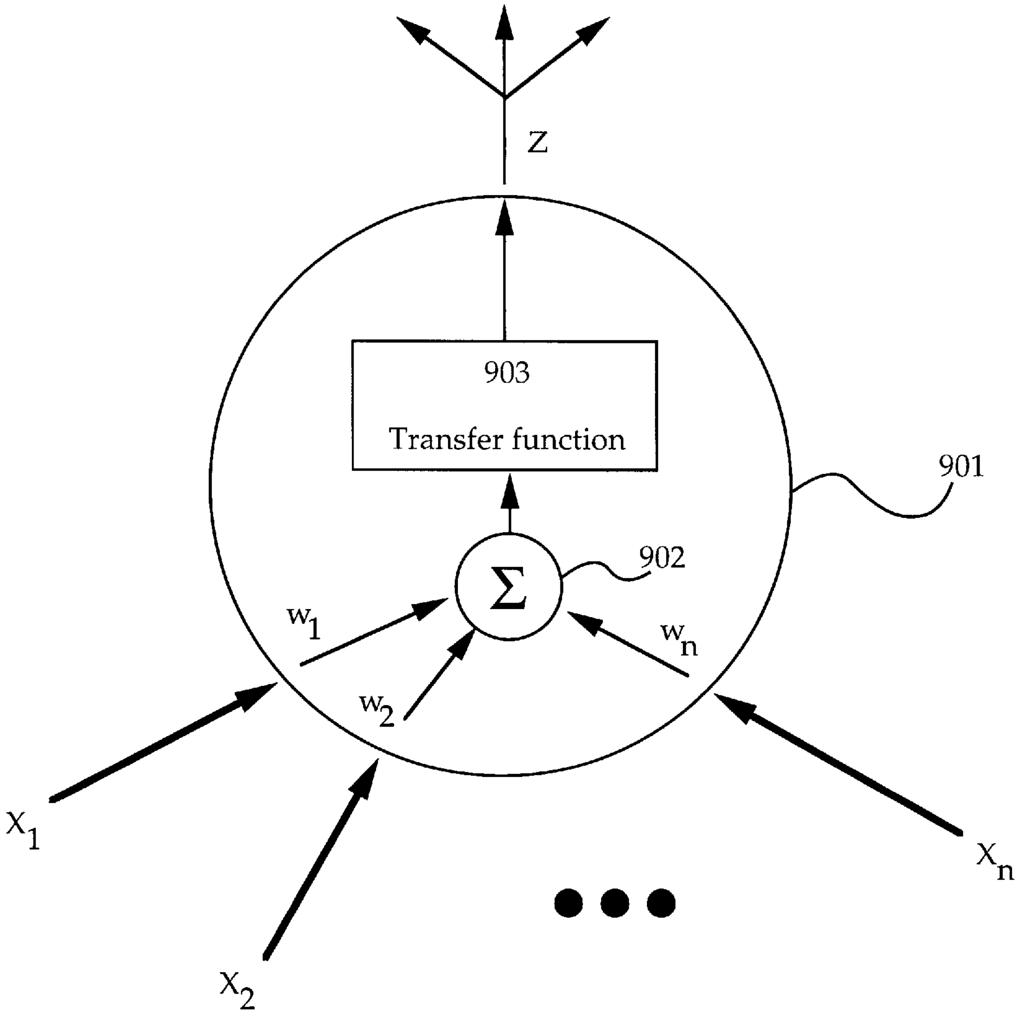


FIGURE 9

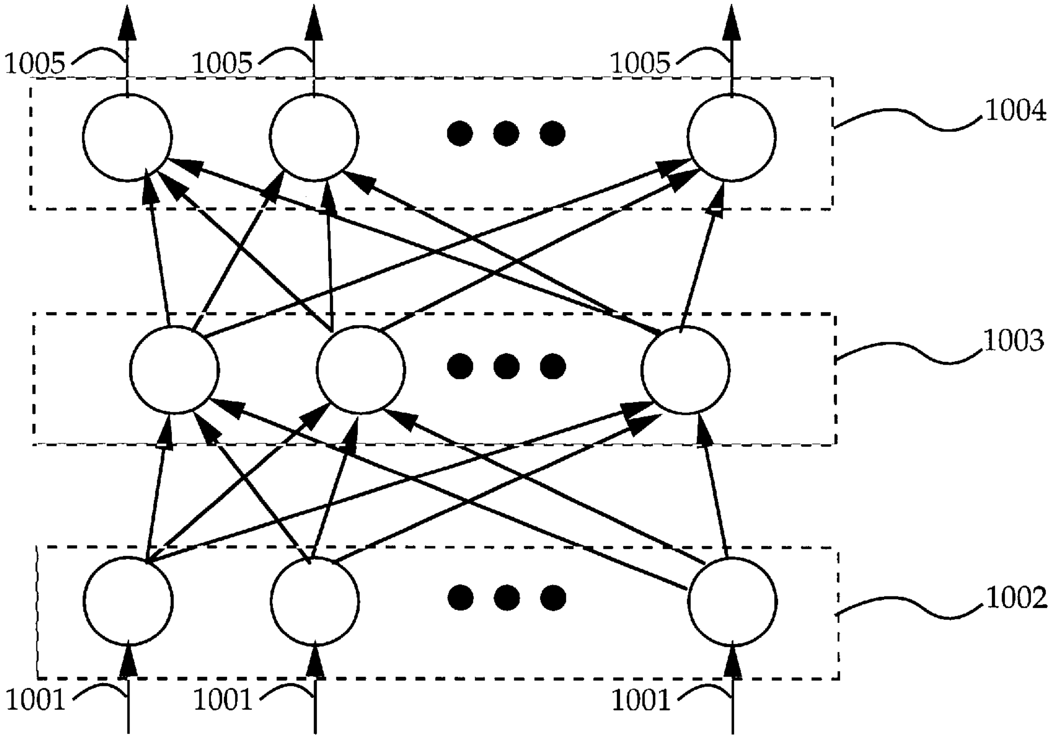


FIGURE 10

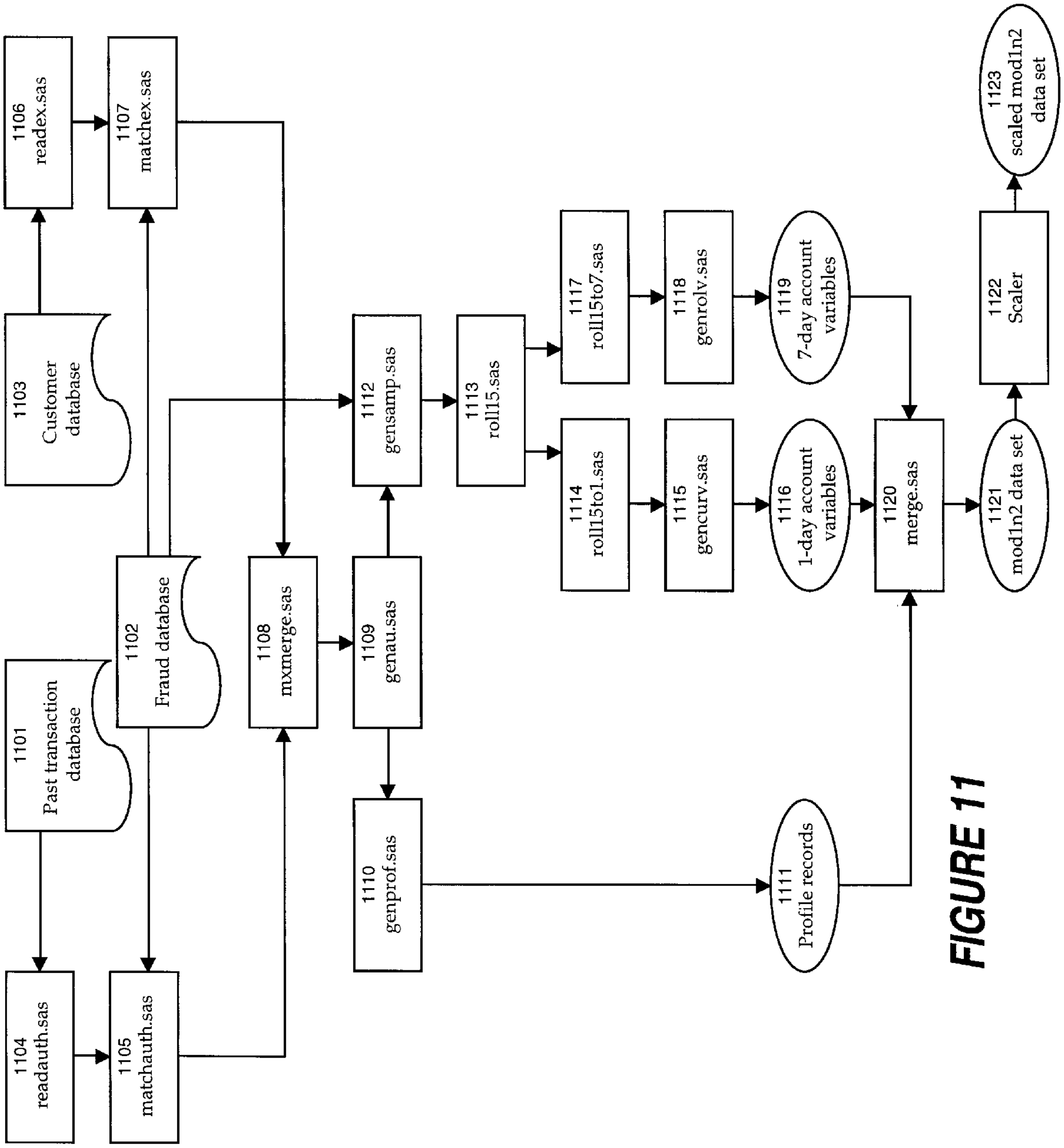

1101
Past transaction database
1102
Fraud database
1103
Customer database
1104
readauth.sas
1105
matchauth.sas
1106
readex.sas
1107
matchex.sas
1108
mxmerge.sas
1109
genau.sas
1110
genprof.sas
1111
Profile records
1112
gensamp.sas
1113
roll15.sas
1114
roll15to1.sas
1115
gencurv.sas
1116
1-day account variables
1117
roll15to7.sas
1118
genrolv.sas
1119
7-day account variables
1120
merge.sas
1121
mod1n2 data set
1122
Scaler
1123
scaled mod1n2 data set

FIGURE 11

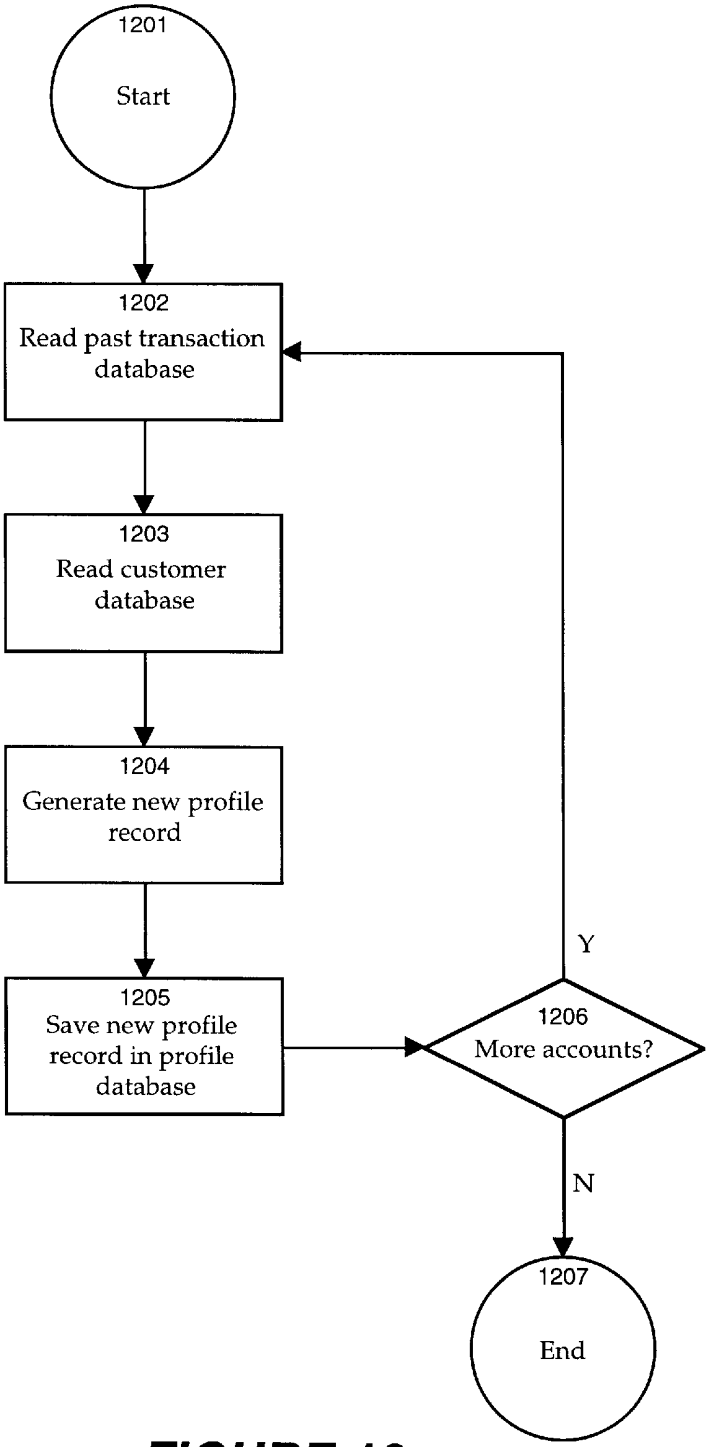

1201
Start
1202
Read past transaction database
1203
Read customer database
1204
Generate new profile record
1205
Save new profile record in profile database
1206
More accounts?
Y
N
1207
End

FIGURE 12

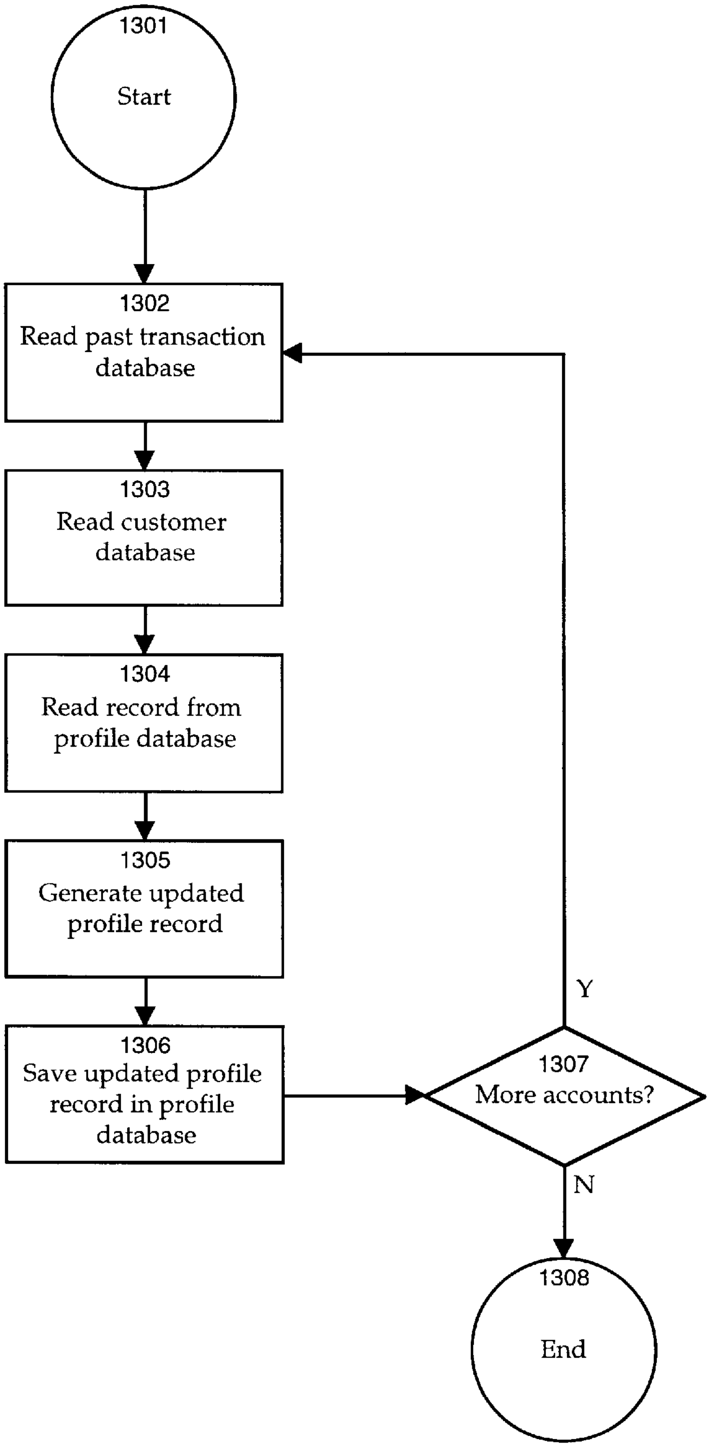

1301
Start
1302
Read past transaction database
1303
Read customer database
1304
Read record from profile database
1305
Generate updated profile record
1306
Save updated profile record in profile database
1307
More accounts?
Y
N
1308
End

FIGURE 13

FIGURE 14

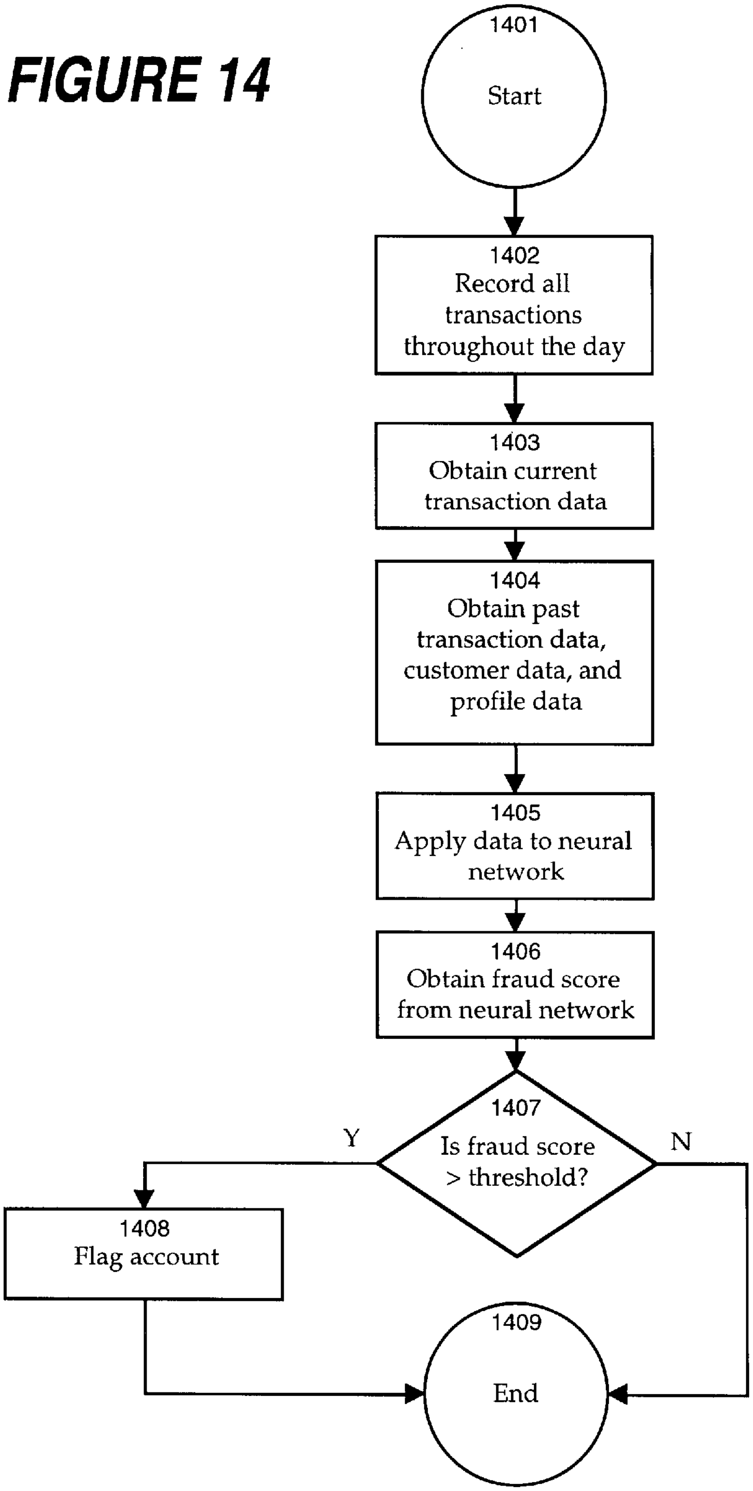

1401
Start
1402
Record all transactions throughout the day
1403
Obtain current transaction data
1404
Obtain past transaction data, customer data, and profile data
1405
Apply data to neural network
1406
Obtain fraud score from neural network
1407
Is fraud score > threshold?
Y
N
1408
Flag account
1409
End

FIGURE 15

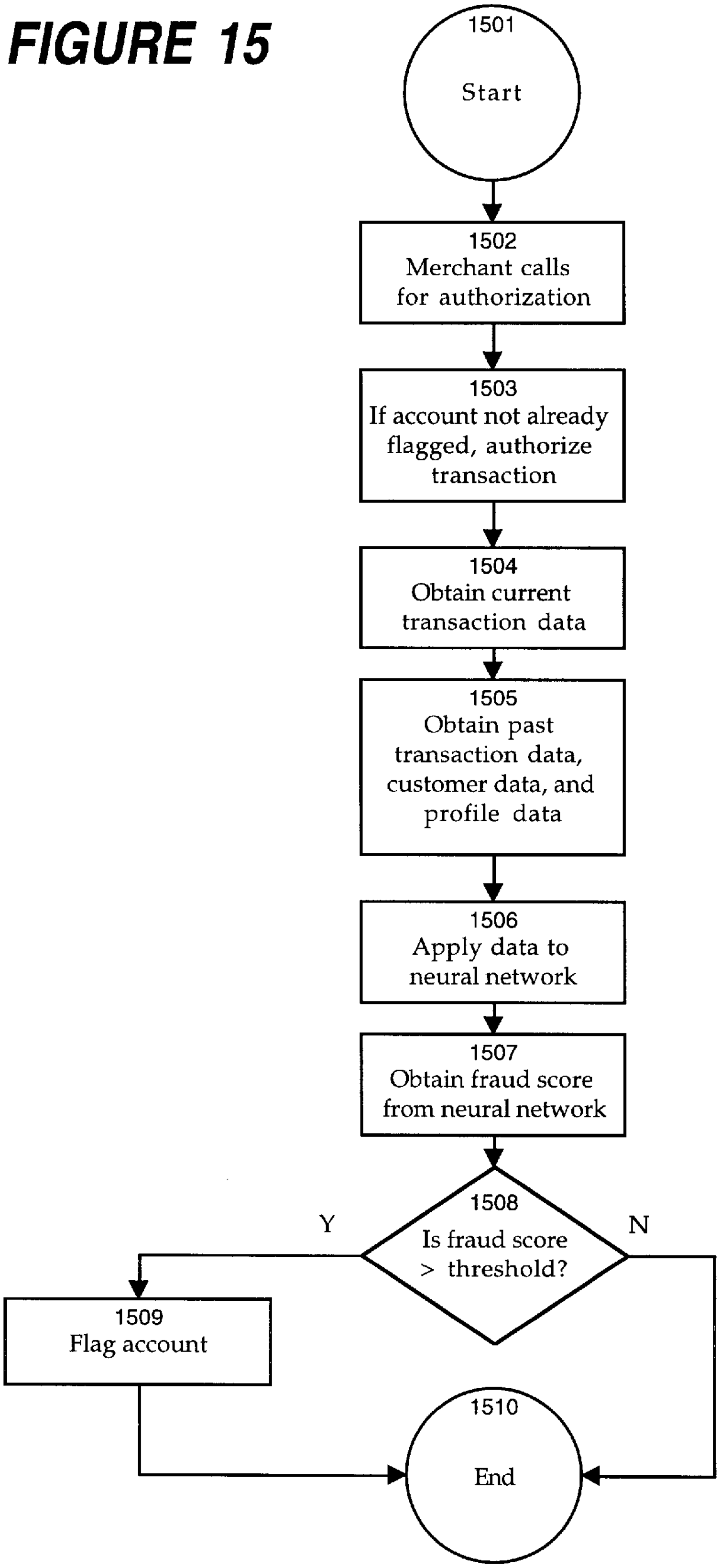
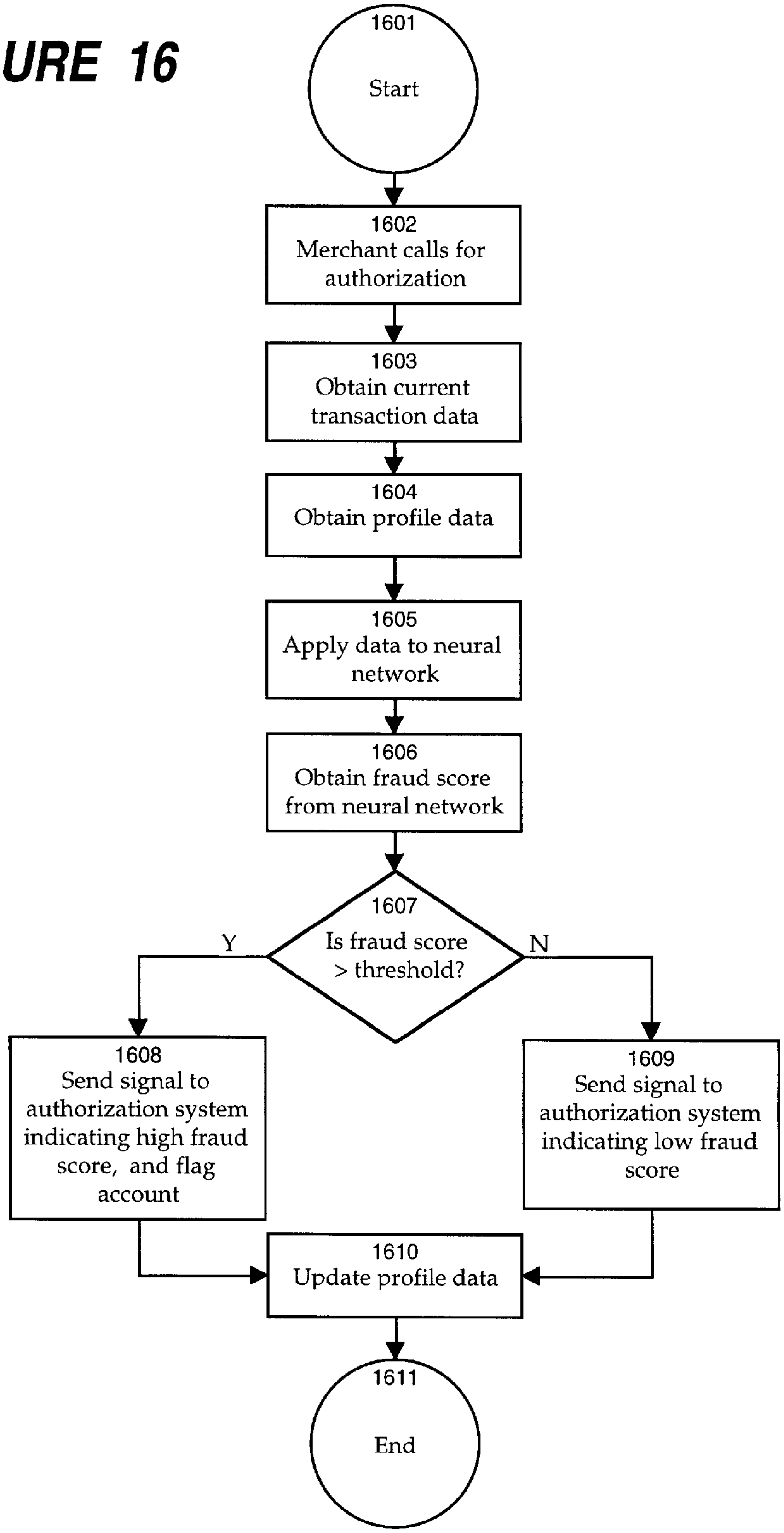

1501
Start
1502
Merchant calls for authorization
1503
If account not already flagged, authorize transaction
1504
Obtain current transaction data
1505
Obtain past transaction data, customer data, and profile data
1506
Apply data to neural network
1507
Obtain fraud score from neural network
1508
Is fraud score > threshold?
Y
N
1509
Flag account
1510
End

FIGURE 16


1601
Start
1602
Merchant calls for authorization
1603
Obtain current transaction data
1604
Obtain profile data
1605
Apply data to neural network
1606
Obtain fraud score from neural network
1607
Is fraud score > threshold?
Y
N
1608
Send signal to authorization system indicating high fraud score, and flag account
1609
Send signal to authorization system indicating low fraud score
1610
Update profile data
1611
End

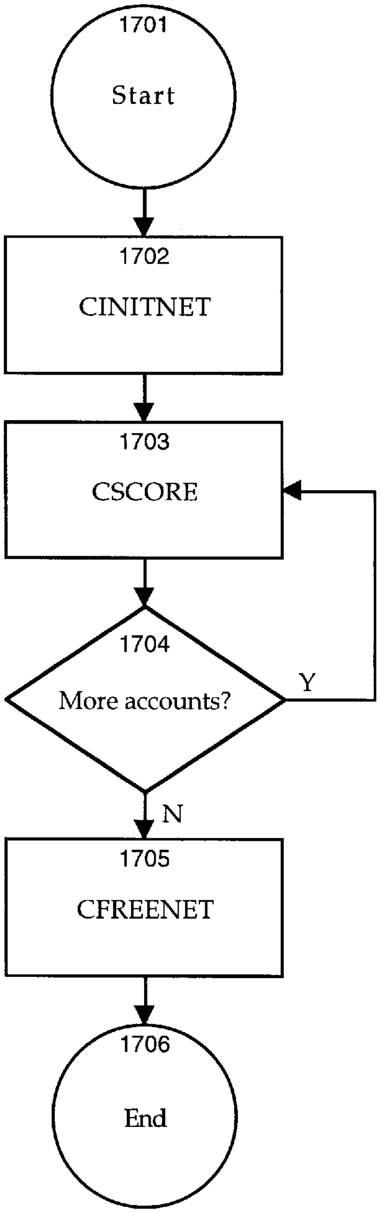

1701
Start
1702
CINITNET
1703
CSCORE
1704
More accounts?
Y
N
1705
CFREENET
1706
End

FIGURE 17

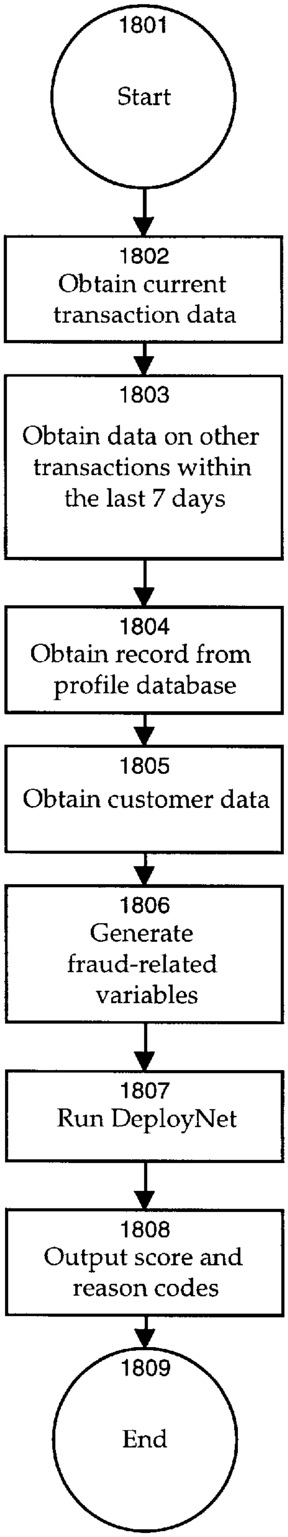

1801
Start
1802
Obtain current transaction data
1803
Obtain data on other transactions within the last 7 days
1804
Obtain record from profile database
1805
Obtain customer data
1806
Generate fraud-related variables
1807
Run DeployNet
1808
Output score and reason codes
1809
End

FIGURE 18

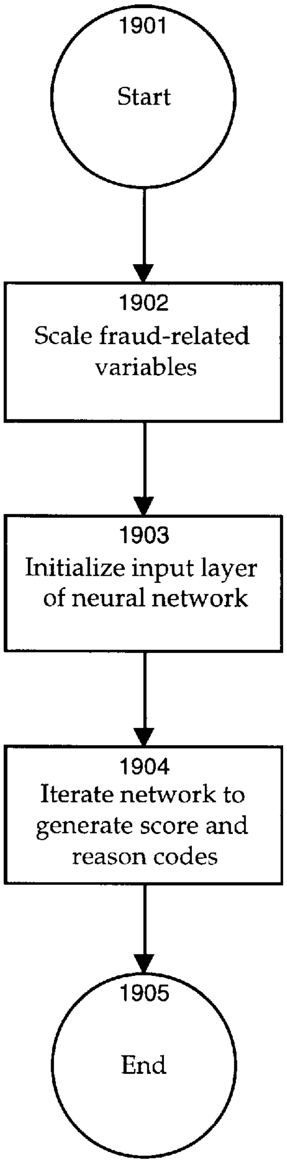

1901
Start
1902
Scale fraud-related variables
1903
Initialize input layer of neural network
1904
Iterate network to generate score and reason codes
1905
End

FIGURE 19

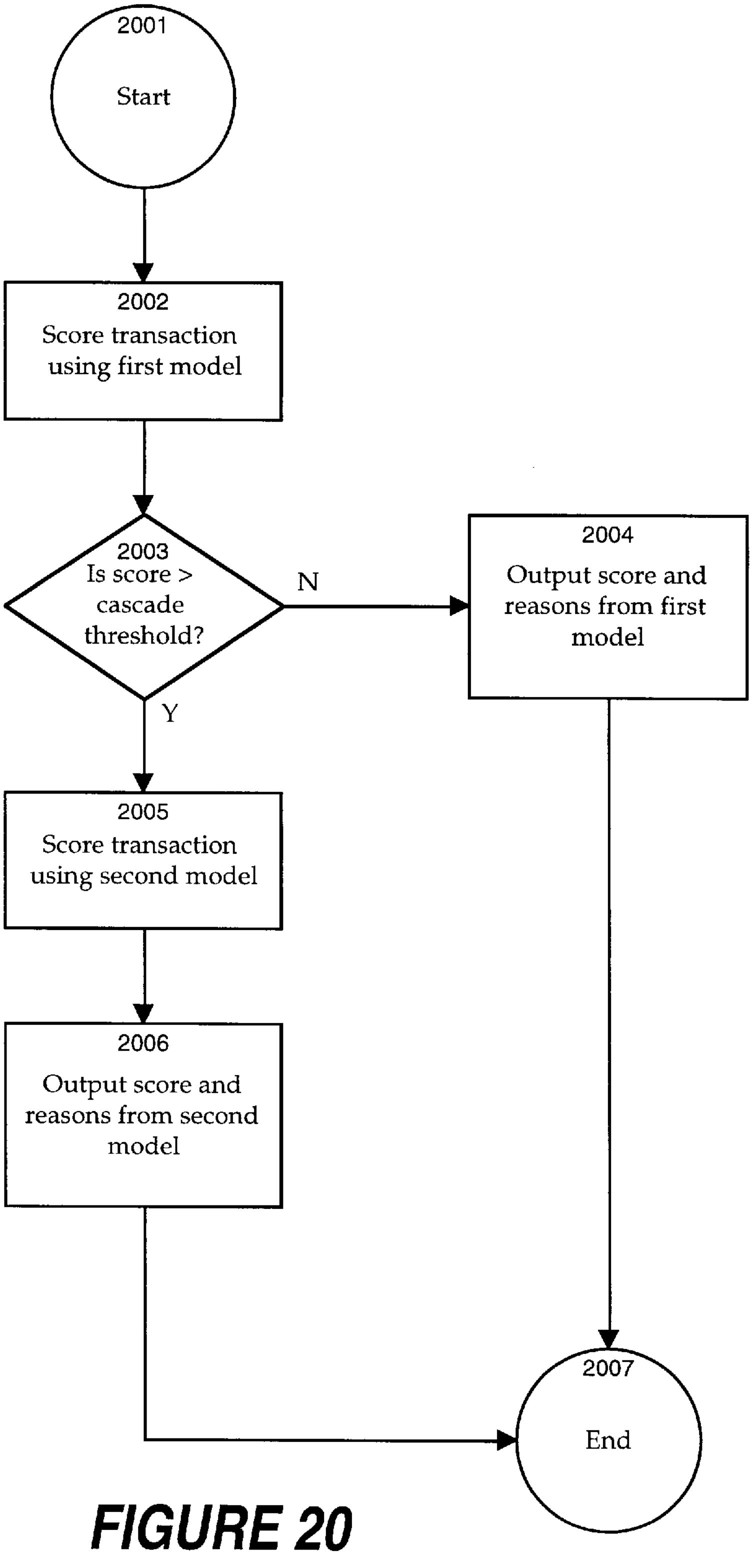
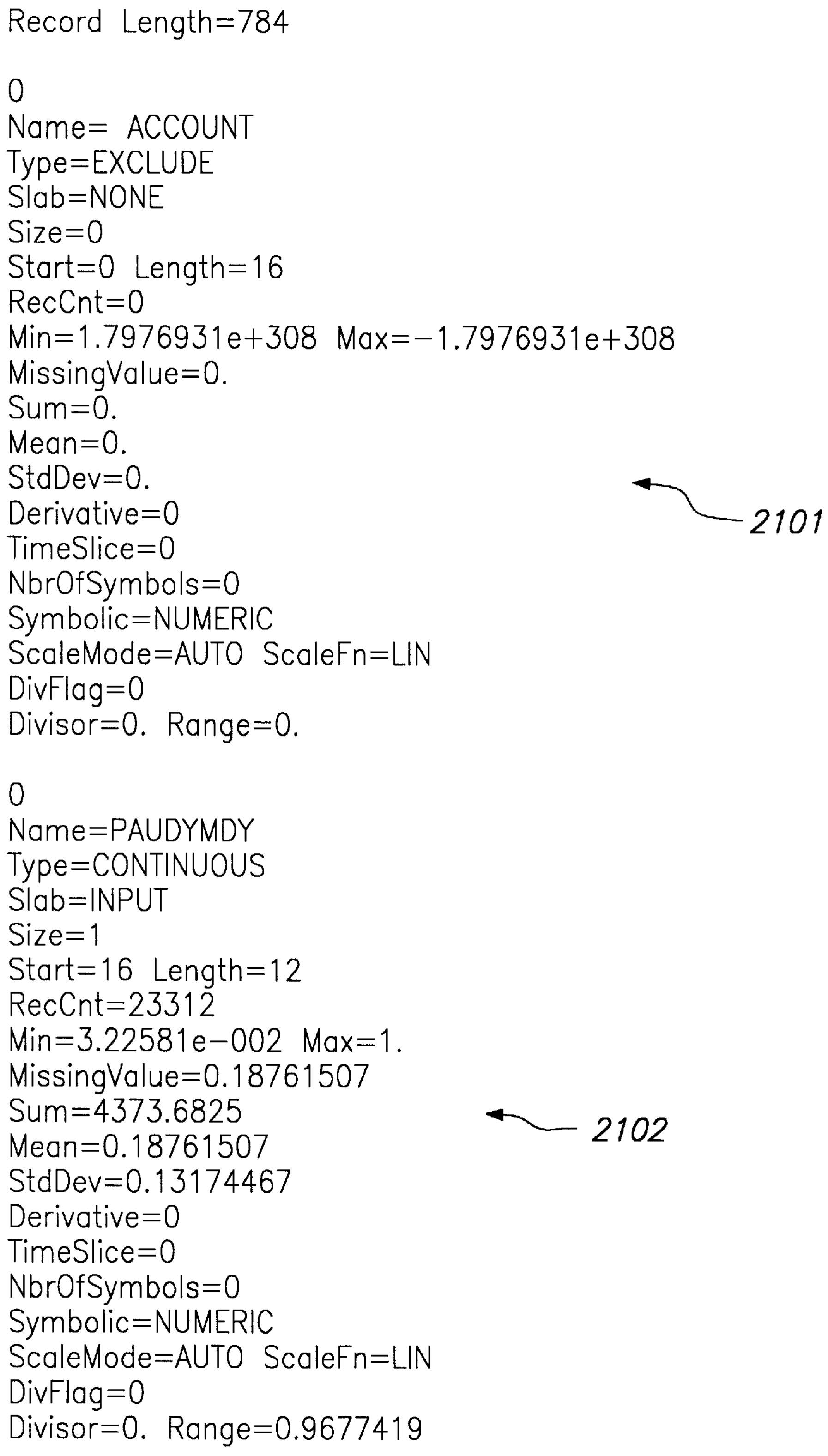

2001
Start
2002
Score transaction using first model
2003
Is score > cascade threshold?
N
Y
2004
Output score and reasons from first model
2005
Score transaction using second model
2006
Output score and reasons from second model
2007
End

FIGURE 20



```
Record Length=784

0
Name= ACCOUNT
Type=EXCLUDE
Slab=NONE
Size=0
Start=0 Length=16
RecCnt=0
Min=1.7976931e+308 Max=-1.7976931e+308
MissingValue=0.
Sum=0.
Mean=0.
StdDev=0.
Derivative=0
TimeSlice=0
NbrOfSymbols=0
Symbolic=NUMERIC
ScaleMode=AUTO ScaleFn=LIN
DivFlag=0
Divisor=0. Range=0.

0
Name=PAUDYMDY
Type=CONTINUOUS
Slab=INPUT
Size=1
Start=16 Length=12
RecCnt=23312
Min=3.22581e-002 Max=1.
MissingValue=0.18761507
Sum=4373.6825
Mean=0.18761507
StdDev=0.13174467
Derivative=0
TimeSlice=0
NbrOfSymbols=0
Symbolic=NUMERIC
ScaleMode=AUTO ScaleFn=LIN
DivFlag=0
Divisor=0. Range=0.9677419
```

FIGURE 21

FRAUD DETECTION USING PREDICTIVE MODELING

CROSS-REFERENCE TO RELATED APPLICATION

U.S. application Ser. No. 07/814,179, (attorney's docket number 726) for "Neural Network Having Expert System Functionality", by Curt A. Levey, filed Dec. 30,1991.

BACKGROUND OF THE INVENTION

1. Field of the Invention

This invention relates generally to the detection of fraudulent use of customer accounts and account numbers, including for example credit card transactions. In particular, the invention relates to an automated fraud detection system and method that uses predictive modeling to perform pattern recognition and classification in order to isolate transactions having high probabilities of fraud.

2. Description of the Related Art

In the following discussion, the term "credit card" will be used for illustrative purposes; however, the techniques and principles discussed herein apply to other types of customer accounts, such as charge cards, bank automated teller machine cards and telephone calling cards.

Credit card issuers conventionally attempt to limit fraud losses by immediately closing a customer's account upon receiving a report that the card has been lost or stolen. Typically, the customer's credit information is then transferred to a new account and a new card is issued. This procedure is only effective in limiting fraudulent use of lost or stolen cards after the loss or theft has been reported to the issuer.

In many cases, however, fraudulent use occurs without the knowledge of the cardholder, and therefore no report is made to the issuer. This may occur if the customer is unaware that the card has been lost or stolen, or if other techniques are employed to perpetrate the fraud, such as: use of counterfeit cards; merchant fraud; application fraud; or interception of credit cards in the mail. In all these situations, the fraudulent use may not be detected until (and unless) the cardholder notices an unfamiliar transaction on his or her next monthly statement and contests the corresponding charge. The concomitant delay in detection of fraud may result in significant losses. User fraud, in which the user claims that a valid transaction is invalid, is also possible.

Issuers of credit cards have sought to limit fraud losses by attempting to detect fraudulent use before the cardholder has reported a lost or stolen card. One conventional technique is known as parameter analysis. A parameter analysis fraud detection scheme makes a decision using a small number of database fields combined in a simple Boolean condition. An example of such a condition is:

> if (number of transactions in 24 hours>X) and (more than Y dollars authorized) then flag this account as high risk

Parameter analysis will provide the values of X and Y that satisfy either the required detection rate or the required false positive rate. In a hypothetical example, parameter values of X=400 and Y=1000 might capture 20% of the frauds with a false positive rate of 200:1, while X=6 and Y=2000 might capture 8% of the frauds with a false positive rate of 20:1.

The rules that parameter analysis provides are easily implemented in a database management system, as they are restricted to Boolean (e.g., and, or) combinations of conditions on single variables.

Parameter analysis derives rules by examining the single variables most able to distinguish fraudulent from non-fraudulent behavior. Since only single-variable threshold comparisons are used, complex interactions among variables are not captured. This is a limitation that could cause the system to discriminate poorly between fraudulent and valid account behavior, resulting in low capture rates and high false-positive rates.

Additionally, an effective fraud detection model generally requires more variables than conventional parameter analysis systems can handle. Furthermore, in order to capture new fraud schemes, parameter analysis systems must be redeveloped often, and automated redevelopment is difficult to implement.

It is desirable, therefore, to have an automated system that uses available information regarding cardholders, merchants, and transactions to screen transactions and isolate those which are likely to be fraudulent, and which captures a relatively high proportion of frauds while maintaining a relatively low false-positive rate. Preferably, such a system should be able to handle a large number of interdependent variables, and should have capability for redevelopment of the underlying system model as new patterns of fraudulent behavior emerge.

SUMMARY OF THE INVENTION

In accordance with the present invention, there is provided an automated system and method for detecting fraudulent transactions, which uses a predictive model such as a neural network to evaluate individual customer accounts and identify potentially fraudulent transactions based on learned relationships among known variables. These relationships enable the system to estimate a probability of fraud for each transaction. This probability may then be provided as output to a human decision-maker involved in processing the transaction, or the issuer may be signaled when the probability exceeds a predetermined amount. The system may also output reason codes that reveal the relative contributions of various factors to a particular result. Finally, the system periodically monitors its performance, and redevelops the model when performance drops below a predetermined level.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram of an implementation of the present invention.

FIG. **2** is a sample system monitor screen which forms part of a typical output interface for the present invention.

FIG. **3** is a sample account selection screen which forms part of a typical output interface for the present invention.

FIG. **4** is a sample transaction analysis screen which forms part of a typical output interface for the present invention.

FIG. **5** is a sample customer information screen which forms part of a typical output interface for the present invention.

FIG. **6** is a sample analyst response screen which forms part of a typical output interface for the present invention.

FIG. **7** is a flowchart illustrating the major functions and operation of the present invention.

FIG. **8** is a block diagram showing the overall functional architecture of the present invention.

FIG. **9** is a diagram of a single processing element within a neural network.

FIG. **10** is a diagram illustrating hidden processing elements in a neural network.

FIG. **11** is a flowchart of the pre-processing method of the present invention.

FIG. **12** is a flowchart of the method of creating a profile record of the present invention.

FIG. **13** is a flowchart of the method of updating a profile record of the present invention.

FIG. **14** is a flowchart showing operation of a batch transaction processing system according to the present invention.

FIG. **15** is a flowchart showing operation of a semi-real-time transaction processing system according to the present invention.

FIG. **16** is a flowchart showing operation of a real-time processing system according to the present invention.

FIG. **17** is a flowchart showing the overall operation of the transaction processing component of the present invention.

FIG. **18** is a flowchart showing the operation of module CSCORE of the present invention.

FIG. **19** is a flowchart showing the operation of DeployNet of the present invention.

FIG. **20** is a flowchart showing cascaded operation of the present invention.

FIG. **21** is a portion of a typical CFG model definition file.

DESCRIPTION OF THE PREFERRED EMBODIMENT

The Figures depict preferred embodiments of the present invention for purposes of illustration only. One skilled in the art will readily recognize from the following discussion that alternative embodiments of the structures and methods illustrated herein may be employed without departing from the principles of the invention described herein.

Referring now to FIG. **1**, there is shown a block diagram of a typical implementation of a system **100** in accordance with the present invention. Transaction information is applied to system **100** via data network **105**, which is connected to a conventional financial data facility **106** collecting transaction information from conventional sources such as human-operated credit-card authorization terminals and automated teller machines (not shown). CPU **101** runs software program instructions, stored in program storage **107**, which direct CPU **101** to perform the various functions of the system. In the preferred embodiment, the software program is written in the ANSI C language, which may be run on a variety of conventional hardware platforms. In accordance with the software program instructions, CPU **101** stores the data obtained from data network **105** in data storage **103**, and uses RAM **102** in a conventional manner as a workspace. CPU **101**, data storage **103**, and program storage **107** operate together to provide a neural network model **108** for predicting fraud. After neural network **108** processes the information, as described below, to obtain an indication of the likelihood of fraud, a signal indicative of that likelihood is sent from CPU **101** to output device **104**.

In the preferred embodiment, CPU **101** is a Model 3090 IBM mainframe computer, RAM **102** and data storage **103** are conventional RAM, ROM and disk storage devices for the Model 3090 CPU, and output device **104** is a conventional means for either printing results based on the signals generated by neural network **108**, or displaying the results on a video screen using a window-based interface system, or sending the results to a database for later access, or sending a signal dependent on the results to an authorization system (not shown) for further processing.

Referring now also to FIGS. **2** through **6**, there are shown sample screens from a conventional window-based interface system (not shown) which forms part of output device **104**. FIG. **2** shows system monitor **201** that allows a fraud analyst or system supervisor to review system performance. System monitor **201** shows a cutoff score **202** above which accounts will be flagged, the number of accounts with scores above the cutoff **203**, and the fraud score **204** and account number **205** for a particular account.

FIG. **3** shows account selection screen **301** that includes a scrolling window **302** allowing the analyst to select high-risk transactions for review, and a set of buttons **303** allowing the analyst to select further operations in connection with the selected transactions.

FIG. **4** shows transaction analysis screen **401** that allows the fraud analyst to examine each high-risk transaction and determine appropriate fraud control actions. It includes account information **402**, fraud score **403**, explanations derived from reason codes **404** that indicate the reasons for fraud score **403**, and two scrolling windows **405** and **406** that show transaction information for the current day and the past seven days **405**, and for the past six months **406**.

FIG. **5** shows customer information screen **501** that allows the analyst to access customer information, including account number **502**, customer names **503**, best time to call **504**, phone numbers **505**, and address **506**. It also provides access to further functions via on-screen buttons **507**.

FIG. **6** shows analyst response screen **601** that allows the analyst to log actions taken to control fraud. It includes a series of check boxes **602** for logging information, a comment box **603**, and on-screen buttons **604** allowing access to other functions.

Referring now also to FIG. **7**, there is shown an overall flowchart illustrating the major functions and operation of the system **100**. First neural network model **108** is trained **701** using data describing past transactions from data network **105**. Then data describing the network model are stored **702**. Once the model description is stored, system **100** is able to process current transactions. System **100** obtains data for a current transaction **703**, and applies the current transaction data to the stored network model **704**. The model **108** determines a fraud score and reason codes (described below), which are output **705** to the user, or to a database, or to another system via output device **104**.

Referring now to FIG. **8**, the overall functional architecture of system **100** is shown. System **100** is broken down into two major components: model development component **801** and transaction processing component **802**. Model development component **801** uses past data **804** to build neural network **108** containing information representing learned relationships among a number of variables. Together, the learned relationships form a model of the behavior of the variables. Although a neural network is used in the preferred embodiment, any type of predictive modeling technique may be used. For purposes of illustration, the invention is described here in terms of a neural network.

Transaction processing component **802** performs three functions: 1) it determines the likelihood of fraud for each transaction by feeding data from various sources **805**, **806** into neural network **108**, obtaining results, and outputting them **807**; 2) when applicable, it creates a record in a profile database **806** summarizing past transactional patterns of the customer; and 3) when applicable, it updates the appropriate record in profile database **806**.

Each of the two components of the system will be described in turn.

Model Development Component **801**

Neural Networks: Neural networks employ a technique of "learning" relationships through repeated exposure to data and adjustment of internal weights. They allow rapid model development and automated data analysis. Essentially, such networks represent a statistical modeling technique that is capable of building models from data containing both linear and non-linear relationships. While similar in concept to regression analysis, neural networks are able to capture nonlinearity and interactions among independent variables without pre-specification. In other words, while traditional regression analysis requires that nonlinearities and interactions be detected and specified manually, neural networks perform these tasks automatically. For a more detailed description of neural networks, see D. E. Rumelhart et al, "Learning Representations by Back-Propagating Errors", *Nature* v. 323, pp. 533–36 (1986), and R. Hecht-Nielsen, "Theory of the Backpropagation Neural Network", in *Neural Networks for Perception*, pp. 65–93 (1992), the teachings of which are incorporated herein by reference.

Neural networks comprise a number of interconnected neuron-like processing elements that send data to each other along connections. The strengths of the connections among the processing elements are represented by weights. Referring now to FIG. **9**, there is shown a diagram of a single processing element **901**. The processing element receives inputs $X_1, X_2, \ldots X_n$, either from other processing elements or directly from inputs to the system. It multiplies each of its inputs by a corresponding weight $w_1, w_2, \ldots w_n$ and adds the results together to form a weighted sum **902**. It then applies a transfer function **903** (which is typically non-linear) to the weighted sum, to obtain a value Z known as the state of the element. The state Z is then either passed on to another element along a weighted connection, or provided as an output signal. Collectively, states are used to represent information in the short term, while weights represent long-term information or learning.

Processing elements in a neural network can be grouped into three categories: input processing elements (those which receive input data values); output processing elements (those which produce output values); and hidden processing elements (all others). The purpose of hidden processing elements is to allow the neural network to build intermediate representations that combine input data in ways that help the model learn the desired mapping with greater accuracy. Referring now to FIG. **10**, there is shown a diagram illustrating the concept of hidden processing elements. Inputs **1001** are supplied to a layer of input processing elements **1002**. The outputs of the input elements are passed to a layer of hidden elements **1003**. Typically there are several such layers of hidden elements. Eventually, hidden elements pass outputs to a layer of output elements **1004**, and the output elements produce output values 1005.

Neural networks learn from examples by modifying their weights. The "training" process, the general techniques of which are well known in the art, involves the following steps:

1) Repeatedly presenting examples of a particular input/output task to the neural network model;

2) Comparing the model output and desired output to measure error; and

3) Modifying model weights to reduce the error.

This set of steps is repeated until further iteration fails to decrease the error. Then, the network is said to be "trained." Once training is completed, the network can predict outcomes for new data inputs.

Fraud-Related Variables: In the present invention, data used to train the model are drawn from various database files containing historical data on individual transactions, merchants, and customers. These data are preferably pre-processed before being fed into the neural network, resulting in the creation of a set of fraud-related variables that have been empirically determined to form more effective predictors of fraud than the original historical data.

Referring now to FIG. **11**, there is shown a flowchart of the pre-processing method of the present invention. Individual elements of the flowchart are indicated by designations which correspond to module names. The following brief description summarizes the processing.

Data used for pre-processing is taken from three databases which contain past data: 1) past transaction database **1101** (also called an "authorization database") containing two years' worth of past transaction data, which may be implemented in the same data base as past data **804**; 2) customer database **1103** containing customer data; and 3) fraud database **1102** which indicates which accounts had fraudulent activity and when the fraudulent activity occurred.

Module readauth.sas **1104** reads transaction data from past transaction database **1101**. Module matchauth.sas **1105** samples this transaction data to obtain a new transaction data set containing all of the fraud accounts and a randomly-selected subset of the non-fraud accounts. In creating the new transaction data set, module matchauth.sas **1105** uses information from fraud database **1102** to determine which accounts have fraud and which do not. For effective network training, it has been found preferable to obtain approximately ten non-fraud accounts for every fraud account.

Module readex.sas **1106** reads customer data from customer database **1103**. Module matchex.sas **1107** samples this customer data to obtain a new customer data set containing all of the fraud accounts and the same subset of non-fraud accounts as was obtained by module matchauth.sas. In creating the new customer data set, module matchex.sas **1107** uses information from fraud database **1102** to determine which accounts have fraud and which do not.

Module mxmerge.sas **1108** merges all of the data sets obtained by modules matchauth.sas **1105** and matchex.sas **1107**. Module genau.sas **1109** subdivides the merged data set into subsets of monthly data.

Module gensamp.sas **1112** samples the data set created by module mxmerge.sas **1108** and subdivided by genau.sas **1109**, and creates a new data set called sample.ssd where each record represents a particular account on a particular day with transaction activity. Module gensamp.sas **1112** determines which records are fraudulent using information from fraud database **1102**. Module gensamp.sas **1112** provides a subset of authorization days, as follows: From the database of all transactions, a set of active account-days is created by removing multiple transactions for the same customer on the same day. In the set of active account-days, each account day is assigned a "draft number" from 0 to 1. This draft number is assigned as follows: If the account-day is non-fraudulent, then the draft number is set to a random number between 0 and 1. If the account-day is fraudulent and it lies on the first or second day of fraud, then the draft number is set to 0. Otherwise, it is set to 1. Then, the 25,000 account-days with the smallest draft numbers are selected for inclusion in sample.ssd. Thus, all fraudulent account-days (up to 25,000) plus a sample of non-fraudulent account-days are included in sample.ssd.

Module roll**15**.sas **1113** generates a 15-day rolling window of data. This data has multiple records for each account-day listed in sample.ssd. The current day and 14 preceding days are listed for each sample account.

Module roll**15**to**7**.sas **1117** takes the roll**15** data set and filters out days eight to 15 to produce roll**7**, a 7-day rolling window data set **1119**. Days eight to 15 are ignored. Module genrolv.sas **1118** generates input variables for a rolling window of the previous 15 days of transactions. It processes a data set with multiple and variable numbers of records per account and produces a data set with one record per account. The result is called rollv.ssd.

Module roll**15**to**1**.sas **1114** takes the roll**15** data set and filters out days except the current day to produce roll**1**. Module gencurv.sas **1115** uses roll**1** to generate current day variables **1116** describing transactions occurring during the current day.

Module genprof.sas generates profile variables which form the profile records **1111**.

Module merge.sas **1120** combines the profile records **1111**, 1-day variables **1116**, and 7-day variables **1119** and generates new fraud-related variables, as listed below, from the combination. It also merges rollv.ssd with the sample-filtered profile data sets to produce a single data set with both profile and rolling window variables: The result is called the mod**1**n**2** data set **1121** (also called the "training set"), which contains the fraud-related variables needed to train the network. Scaler module **1122** scales the variables such that the mean value for each variable in the scaled training set is 0.0 and the standard deviation is 1.0, to create scaled mod**1**n**2** data set **1123**.

Many fraud-related variables may be generated using variations of the pre-processing method described above. Fraud-related variables used in the preferred embodiment include:

Customer usage pattern profiles representing time-of-day and day-of-week profiles;

Expiration date for the credit card;

Dollar amount spent in each SIC (Standard Industrial Classification) merchant group category during the current day;

Percentage of dollars spent by a customer in each SIC merchant group category during the current day;

Number of transactions in each SIC merchant group category during the current day;

Percentage of number of transactions in each SIC merchant group category during the current day;

Categorization of SIC merchant group categories by fraud rate (high, medium, or low risk);

Categorization of SIC merchant group categories by customer types (groups of customers that most frequently use certain SIC categories);

Categorization of geographic regions by fraud rate (high, medium, or low risk);

Categorization of geographic regions by customer types;

Mean number of days between transactions;

Variance of number of days between transactions;

Mean time between transactions in one day;

Variance of time between transactions in one day;

Number of multiple transaction declines at same merchant;

Number of out-of-state transactions;

Mean number of transaction declines;

Year-to-date high balance;

Transaction amount;

Transaction date and time;

Transaction type.

Additional fraud-related variables which may also be considered are listed below:

Current Day Cardholder Fraud Related Variables

bweekend	current day boolean indicating current datetime considered weekend
cavapvdl	current day mean dollar amount for an approval
cavapvdl	current day mean dollar amount for an approval
cavaudl	current day mean dollars per auth across day
ccoscdoni	current day cosine of the day of month i.e. cos(day ((datepart(cst_dt) * &TWOPI)/30));
ccoscdow	current day cosine of the day of week i.e. cos(weekday ((datepart(cst_dt) * &TWOPI)/7));
ccoscmoy	current day cosine of the month of year i.e. cos(month ((datepart(cst_dt) * &TWOPI)/12));
cdom	current day day of month
cdow	current day day of week
chdzip	current cardholder zip
chibal	current day high balance
chidcapv	current day highest dollar amt on a single cash approve
chidcdec	current day highest dollar amt on a single cash decline
chidmapv	current day highest dollar amt on a single merch approve
chidmdec	current day highest dollar amt on a single merch decline
chidsapv	current day highest dollar amount on a single approve
chidsau	current day highest dollar amount on a single auth
chidsdec	current day highest dollar amount on a single decline
cmoy	current day month of year
cratdcau	current day ratio of declines to auths
csincdom	current day sine of the day of month i.e. sin(day ((datepart(cst_dt) * &TWOPI)/30));
csincdow	current day sine of the day of week i.e. sin(weekday ((datepart(cst_dt) * &TWOPI)/7)),
csincmoy	current day sine of the month of year i.e: sin(month ((datepart(cs_dt) * &TWOPI)/12));
cst_dt	current day cst datetime derived from zip code and CST auth time
ctdapv	current day total dollars of approvals
ctdau	current day total dollars of auths
ctdcsapv	current day total dollars of cash advance approvals
ctdcsdec	current day total dollars of cash advance declines
ctddec	current day total dollars of declines
ctdmrapv	current day total dollars of merchandise approvals
ctdmrdec	current day total dollars of merchandise declines
ctnapv	current day total number of approves
ctnau	current day total number of auths
ctnau10d	current day number of auths in day <=$10

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ctnaudy	current day total number of auths in a day
ctncsapv	current day total number of cash advance approvals
ctncsapv	current day total number of cash approves
ctncsdec	current day total number of cash advance declines
ctndec	current day total number of declines
cmmrapv	current day total number of merchandise approvals
ctnmrdec	current day total number of merchandise declines
ctnsdapv	current day total number of approvals on the same day of week as current day
ctnwdaft	current day total number of weekday afternoon approvals
ctnwdapv	current day total number of weekday approvals
ctnwdeve	current day total number of weekday evening approvals
ctnwdmor	current day total number of weekday morning approvals
ctnwdnit	current day total number of weekday night approvals
ctnweaft	current day total number of weekend afternoon approvals
ctnweapv	current day total number of weekend approvals
ctnweeve	current day total number of weekend evening approvals
ctnwemor	current day total number of weekend morning approvals
ctnwenit	current day total number of weekend night approvals
currbal	current day current balance
cvraud1	current day variance of dollars per auth across day
czrate1	current day zip risk group 1 'Zip very high fraud rate'
czrate2	current day zip risk group 2 'Zip high fraud rate'
czrate3	current day zip risk group 3 'Zip medium high fraud rate'
czrate4	current day zip risk group 4 'Zip medium fraud rate'
czrate5	current day zip risk group 5 'Zip medium low fraud rate'
czrate6	current day zip risk group 6 'Zip low fraud rate'
czrate7	current day zip risk group 7 'Zip very low fraud rate'
czrate8	current day zip risk group 8 'Zip unknown fraud rate'
ctdsfa01	current day total dollars of transactions in SIC factor group 01
ctdsfa02	current day total dollars of transactions in SIC factor group 02
ctdsfa03	current day total dollars of transactions in SIC factor group 03
ctdsfa04	current day total dollars of transactions in SIC factor group 04
ctdsfa05	current day total dollars of transactions in SIC factor group 05
ctdsfa06	current day total dollars of transactions in SIC factor group 06
ctdsfa07	current day total dollars of transactions in SIC factor group 07
ctdsfa08	current day total dollars of transactions in SIC factor group 08
ctdsfa09	current day total dollars of transactions in SIC factor group 09
ctdsfa10	current day total dollars of transactions in SIC factor group 10
ctdsfa11	current day total dollars of transactions in SIC factor group 11
ctdsra01	current day total dollars of transactions in SIC fraud rate group 01
ctdsra02	current day total dollars of transactions in SIC fraud rate group 02
ctdsra03	current day total dollars of transactions in SIC fraud rate group 03
ctdsra04	current day total dollars of transactions in SIC fraud rate group 04
ctdsra05	current day total dollars of transactions in SIC fraud rate group 05
ctdsra06	current day total dollars of transactions in SIC fraud rate group 06
ctdsra07	current day total dollars of transactions in SIC fraud rate group 07
ctdsva01	current day total dollars in SIC VISA group 01
ctdsva02	current day total dollars in SIC VISA group 02
ctdsva03	current day total dollars in SIC VISA group 03
ctdsva04	current day total dollars in SIC VISA group 04
ctdsva05	current day total dollars in SIC VISA group 05
ctdsva06	current day total dollars in SIC VISA group 06
ctdsva07	current day total dollars in SIC VISA group 07
ctdsva08	current day total dollars in SIC VISA group 08
ctdsva09	current day total dollars in SIC VISA group 09
ctdsva10	current day total dollars in SIC VISA group 10
ctdsva11	current day total dollars in SIC VISA group 11
ctnsfa01	current day total number of transactions in SIC factor group 01
ctnsfa02	current day total number of transactions in SIC factor group 02
ctnsfa03	current day total number of transactions in SIC factor group 03
ctnsfa04	current day total number of transactions in SIC factor group 04
ctnsfa05	current day total number of transactions in SIC factor group 05
ctnsfa06	current day total number of transactions in SIC factor group 06
ctnsfa07	current day total number of transactions in SIC factor group 07
ctnsfa08	current day total number of transactions in SIC factor group 08
ctnsfa09	current day total number of transactions in SIC factor group 09
ctnsfa10	current day total number of transactions in SIC factor group 10
ctnsfa11	current day total number of transactions in SIC factor group 11
ctnsra01	current day total number of transactions in SIC fraud rate group 01
ctnsra02	current day total number of transactions in SIC fraud rate group 02
ctnsra03	current day total number of transactions in SIC fraud rate group 03
ctnsra04	current day total number of transactions in SIC fraud rate group 04
ctnsra05	current day total number of transactions in SIC fraud rate group 05
ctnsra06	current day total number of transactions in SIC fraud rate group 06
ctnsra07	current day total number of transactions in SIC fraud rate group 07
ctnsva01	current day total number in SIC VISA group 01
ctnsva02	current day total number in SIC VISA group 02
ctnsva03	current day total number in SIC VISA group 03
ctnsva04	current day total number in SIC VISA group 04
ctnsva05	current day total number in SIC VISA group 05

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ctnsva06	current day total number in SIC VISA group 06
ctnsva07	current day total number in SIC VISA group 07
ctnsva08	current day total number in SIC VISA group 08
ctnsva09	current day total number in SIC VISA group 09
ctnsva10	current day total number in SIC VISA group 10
ctnsva11	current day total number in SIC VISA group 11
	7 Day Cardholer Fraud Related Variables
raudymdy	7 day ratio of auth days over number of days in the window
ravapvdl	7 day mean dollar amount for an approval
ravaudl	7 day mean dollars per auth across window
rddapv	7 day mean dollars per day of approvals
rddapv2	7 day mean dollars per day of approvals on days with auths
rddau	7 day mean dollars per day of auths on days with auths
rddauall	7 day mean dollars per day of auths on all days in window
rddcsapv	7 day mean dollars per day of cash approvals
rddcsdec	7 day mean dollars per day of cash declines
rdddec	7 day mean dollars per day of declines
rdddec2	7 day mean dollars per day of declines on days with auths
rddmrapv	7 day mean dollars per day of merchandise approvals
rddmrdec	7 day mean dollars per day of merchandise declines
rdnapv	7 day mean number per day of approvals
rdnau	7 day mean number per day of auths on days with auths
rdnauall	7 day mean number per day of auths on all days in window
rdncsapv	7 day mean number per day of cash approvals
rdncsdec	7 day mean number per day of cash declines
rdndec	7 day mean number per day of declines
rdnmrapv	7 day mean number per day of merchandise approvals
rdnmrdec	7 day mean number per day of merchandise declines
rdnsdap2	7 day mean number per day of approvals on same day of week calculated only for those days which had approvals
rdnsdapv	7 day mean number per day of approvals on same day of week as current day
rdnwdaft	7 day mean number per day of weekday afternoon approvals
rdnwdapv	7 day mean number per day of weekday approvals
rdnwdeve	7 day mean number per day of weekday evening approvals
rdnwdmor	7 day mean number per day of weekday morning approvals
rdnwdnit	7 day mean number per day of weekday night approvals
rdnweaft	7 day mean number per day of weekend afternoon approvals
rdnweapv	7 day mean number per day of weekend approvals
rdnweeve	7 day mean number per day of weekend evening approvals
rdnwemor	7 day mean number per day of weekend morning approvals
rdnwenit	7 day mean number per day of weekend night approvals
rhibal	7 day highest window balance
rhidcapv	7 day highest dollar amt on a single cash approve
rhidcdec	7 day highest dollar amt on a single cash decline
rhidmapv	7 day highest dollar amt on a single merch approve
rhidmdec	7 day highest dollar amt on a single merch decline
rhidsapv	7 day highest dollar amount on a single approve
rhidsam	7 day highest dollar amount on a single auth
rhidsdec	7 day highest dollar amount on a single decline
rhidtapv	7 day highest total dollar amount for an approve in a single day
rhidtau	7 day highest total dollar amount for any auth in a single day
rhidtdec	7 day highest total dollar amount for a decline in a single day
rhinapv	7 day highest number of approves in a single day
rhinau	7 day highest number of auths in a single day
rhindec	7 day highest number of declines in a single day
rnaudy	7 day number of days in window with any auths
rnausd	7 day number of same day of week with any auths
rnauwd	7 day number of weekdays days in window with any auths
rnauwe	7 day number of weekend days in window with any auths
rncsaudy	7 day number of days in window with cash auths
rnmraudy	7 day number of days in window with merchant auths
rtdapv	7 day total dollars of approvals
rtdau	7 day total dollars of auths
rtdcsapv	7 day total dollars of cash advance approvals
rtdcsdec	7 day total dollars of cash advance declines
rtddec	7 day total dollars of declines
rtdmrapv	7 day total dollars of merchandise approvals
rtdmrdec	7 day total dollars of merchandise declines
rtnapv	7 day total number of approvals
rtnapvdy	7 day total number of approvals in a day
rtnan	7 day total number of auths
rtnau10d	7 day number of auths in window <= $10
rtncsapv	7 day total number of cash advance approvals
rtncsdec	7 day total number of cash advance adeclines
rtndec	7 day total number of declines
rtnmrapv	7 day total number of merchandise approvals
rtnmrdec	7 day total number of merchandise declines
rtnsdapv	7 day total number of approvals on the same day of week as current day
rtnwdaft	7 day total number of weekday afternoon approvals

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rtnwdapv	7 day total number of weekday approvals
rtnwdeve	7 day total number of weekday evening approvals
rtnwdmor	7 day total number of weekday morning approvals
rtnwdnit	7 day total number of weekday night approvals
rtnweaft	7 day total number of weekend afternoon approvals
rtnweapv	7 day total number of weekend approvals
rtnweeve	7 day total number of weekend evening approvals
rtnwemor	7 day total number of weekend morning approvals
rtnwenit	7 day total number of weekend night approvals
rvraudl	7 day variance of dollars per auth across window
	Profile Cardholder Fraud Related Variables
paudymdy	profile ratio of auth days over number of days in the month
pavapvdl	profile mean dollar amount for an approval
pavaudl	profile mean dollars per auth across month
pchdzip	profile the last zip of the cardholder
pdbm	profile value of 'date became member' at time of last profile update
pddapv	profile daily mean dollars of approvals
pddapv2	profile daily mean dollars of approvals on days with auths
pddau	profile daily mean dollars of auths on days with auths
pddau30	profile daily mean dollars of auths on all days in month
pddcsapv	profile daily mean dollars of cash approvals
pddcsdec	profile daily mean dollars of cash declines
pdddec	profile daily mean dollars of declines
pdddec2	profile daily mean dollars of declines on days with auths
pddmrapv	profile daily mean dollars of merchandise approvals
pddmrdec	profile daily mean dollars of merchandise declines
pdnapv	profile daily mean number of approvals
pdnau	profile daily mean number of auths on days with auths
pdnau30	profile daily mean number of auths on all days in month
pdncsapv	profile daily mean number of cash approvals
pdncsdec	profile daily mean number of cash declines
pdndec	profile daily mean number of declines
pdnmrapv	profile daily mean number of merchandise approvals
pdnmrdec	profile daily mean number of merchandise declines
pdnw1ap2	profile mean number of approvals on Sundays which had auths
pdnw1apv	profile mean number of approvals on Sundays (day 1 of week)
pdnw2ap2	profile mean number of approvals on Mondays which had auths
pdnw2apv	profile mean number of approvals on Mondays (day 2 of week)
pdnw3ap2	profile mean number of approvals on Tuesdays which had auths
pdnw3apv	profile mean number of approvals on Tuesdays (day 3 of week)
pdnw4ap2	profile mean number of approvals on Wednesdays which had auths
pdnw4apv	profile mean number of approvals on Wednesdays (day 4 of week)
pdnw5ap2	profile mean number of approvals on Thursdays which had auths
pdnw5apv	profile mean number of approvals on Thursdays (day 5 of week)
pdnw6ap2	prdfile mean number of approvals on Fridays which had auths
pdnw6apv	profile mean number of approvals on Fridays (day 6 of week)
pdnw7ap2	profile mean number of approvals on Saturdays which had auths
pdnw7apv	profile mean number of approvals on Saturdays (day 7 of week)
pdnwdaft	profile daily mean number of weekday afternoon approvals
pdnwdapv	profile daily mean number of weekday approvals
pdnwdeve	profile daily mean number of weekday evening approvals
pdnwdmor	profile daily mean number of weekday morning approvals
pdnwdnit	profile daily mean number of weekday night approvals
pdnweaft	profile daily mean number of weekend afternoon approvals
pdnweapv	profile daily mean number of weekend approvals
pdnweeve	profile daily mean number of weekend evening approvals
pdnwemor	profile daily mean number of weekend morning approvals
pdnwenit	profile daily mean number of weekend night approvals
pexpir	profile expiry date stored in profile; update if curr date>pexpir
phibal	profile highest monthly balance
phidcapv	profile highest dollar amt on a single cash approve in a month
phidcdec	profile highest dollar amt on a single cash decline in a month
phidmapv	profile highest dollar amt on a single merch approve in a month
phidmdec	profile highest dollar amt on a single merch decline in a month
phidsapv	profile highest dollar amount on a single approve in a month
phidsau	profile highest dollar amount on a single auth in a month
phidsdec	profile highest dollar amount on a single decline in a month
phidtapv	profile highest total dollar amount for an approve in a single day
phidtau	profile highest total dollar amount for any auth in a single day
phidtdec	profile highest total dollar amount for a decline in a single day
phinapv	profile highest number of approves in a single day
phinau	profile highest number of auths in a single day
phindec	profile highest number of declines in a single day
pm1avbal	profile average bal. during 1st 10 days of mo.
pm1nauths	profile number of auths in the 1st 10 days of mo.
pm2avbal	profile average bal. during 2nd 10 days of mo.
pm2nauths	profile number of auths in the 2nd 10 days of mo.
pm3avbal	profile average bal. during remaining days
pm3nauths	profile number of auths in the last part of the month.

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pmovewt	profile uses last zip to determine recent residence move; pmovewt =2 for a move within the previous calendar month; pmovew
pnaudy	profile number of days with auths
pnauw1	profile number of Sundays in month with any auths
pnauw2	profile number of Mondays in month with any auths
pnauw3	profile number of Tuesdays in month with any auths
pnauw4	profile number of Wednesdays in month with any auths
pnauw5	profile number of Thursdays in month with any auths
pnauw6	profile number of Fridays in month with any auths
pnauw7	profile number of Saturdays in month with any auths
pnauwd	profile number of weekday days in month with any auths
pnauwe	profile number of weekend days in month with any auths
pncsaudy	profile number of days in month with cash auths
pnmraudy	profile number of days in month with merchant auths
pnweekday	profile number of weekday days in the month
pnweekend	profile number of weekend days in the month
pratdcau	profile ratio of declines to auths
profage	profile number of months this account has had a profile (up to 6 mo.)
psdaudy	profile standard dev. of # days between transactions in a month
psddau	profile standard dev. of $ per auth in a month
ptdapv	profile total dollars of approvals in a month
ptdau	profile total dollars of auths in a month
ptdaudy	profile total dollars of auths in a day
ptdcsapv	profile total dollars of eash advance approvals in a month
ptdcsdec	profile total dollars of cash advance declines in a month
ptddec	profile total dollars of declines in a month
ptdmrapv	profile total dollars of merchandise approvals in a month
ptdmrdec	profile total dollars of merchandise declines in a month
ptdsfa01	profile total dollars of transactions in SIC factor group 01
ptdsfa02	profile total dollars of transactions in SIC factor group 02
ptdsfa03	profile total dollars of transactions in SIC factor group 03
ptdsfa04	profile total dollars of transactions in SIC factor group 04
ptdsfa05	profile total dollars of transactions in SIC factor group 05
ptdsfa06	profile total dollars of transactions in SIC factor group 06
ptdsfa07	profile total dollars of transactions in SIC factor group 07
ptdsfa08	profile total dollars of transactions in SIC factor group 08
ptdsfa09	profile total dollars of transactions in SIC factor group 09
ptdsfa10	profile total dollars of transactions in SIC factor group 10
ptdsfa11	profile total dollars of transactions in SIC factor group 11
ptdsra01	profile total dollars of transactions in SIC fraud rate group 01
ptdsra02	profile total dollars of transactions in SIC fraud rate group 02
ptdsra03	profile total dollars of transactions in SIC fraud rate group 03
ptdsra04	profile total dollars of transactions in SIC fraud rate group 04
ptdsra05	profile total dollars of transactions in SIC fraud rate group 05
ptdsra06	profile total dollars of transactions in SIC fraud rate group 06
ptdsra07	profile total dollars of transactions in SIC fraud rate group 07
ptdsva01	profile total dollars in SIC VISA group 01
ptdsva02	profile total dollars in SIC VISA group 02
ptdsva03	profile total dollars in SIC VISA group 03
ptdsva04	profile total dollars in SIC VISA group 04
ptdsva05	profile total dollars in SIC VISA group 05
ptdsva06	profile total dollars in SIC VISA group 06
ptdsva07	profile total dollars in SIC VISA group 07
ptdsva08	profile total dollars in SIC VISA group 08
ptdsva09	profile total dollars in SIC VISA group 09
ptdsva10	profile total dollars in SIC VISA group 10
ptdsva11	profile total dollars in SIC VISA group 11
ptnapv	profile total number of approvals in a month
ptnapvdy	profile total number of approves a day
ptnau	profile total number of auths in a month
ptnau10d	profile number of auths in month <= $10
ptnaudy	profile total number of auths in a day
ptncsapv	profile total number of cash advance approvals in a month
ptncsdec	profile total number of cash advance declines in a month
ptndec	profile total number of declines in a month
ptndecdy	profile total number of declines in a day
ptnmrapv	profile total nurnher of merchandise approvals in a month
ptnmrdec	profile total number of merchandise declines in a month
ptnsfa01	profile total number of transactions in SIC factor group 01
ptnsfa02	profile total number of transactions in SIC factor group 02
ptnsfa03	profile total number of transactions in SIC factor group 03
ptnsfa04	profile total number of transactions in SIC factor group 04
ptnsfa05	profile total number of transactions in SIC factor group 05
ptnsfa06	profile total number of transactions in SIC factor group 06
ptnsfa07	profile total number of transactions in SIC factor group 07
ptnsfa08	profile total number of transactions in SIC factor group 08
ptnsfa09	profile total number of taansactions in SIC factor group 09
ptnsfa10	profile total number of transactions in SIC factor group 10
ptnsfa11	profile total number of transactions in SIC factor group 11
ptnsra01	profile total number of transactions in SIC fraud rate group 01

-continued

ptnsra02	profile total number of transactions in SIC fraud rate group 02
ptnsra03	profile total number of transactions in SIC fraud rate group 03
ptnsra04	profile total number of transactions in SIC fraud rate group 04
ptnsra05	profile total number of taansactions in SIC fraud rate group 05
ptnsra06	profile total number of transactions in SIC fraud rate group 06
ptnsra07	profile total number of transactions in SIC fraud rate group 07
ptnsva01	profile total number in SIC VISA group 01
ptnsva02	profile total number in SIC VISA group 02
ptnsva03	profile total number in SIC VISA group 03
ptnsva04	profile total number in SIC VISA group 04
ptnsva05	profile total number in SIC VISA group 05
ptnsva06	profile total number in SIC VISA group 06
ptnsva07	profile total number in SIC VISA group 07
ptnsva08	profile total number in SIC VISA group 08
ptnsva09	profile total number in SIC VISA group 09
ptnsva10	profile total number in SIC VISA group 10
ptnsva11	profile total number in SIC VISA group 11
ptnw1apv	profile total number of approvals on Sundays (day 1 of week)
ptnw2apv	profile total number of approvals on Mondays (day 2 of week)
ptnw3apv	profile total number of approvals on Tuesdays (day 3 of week)
ptnw4apv	profile total number of approvals on Wednesdays (day 4 of week)
ptnw5apv	profile total number of approvals on Thursdays (day 5 of week)
ptnw6apv	profile total number of approvals on Fridays (day 6 of week)
ptnw7apv	profile total number of approvals on Saturdays (day 7 of week)
ptnwdaft	profile total number of weekday afternoon approvals in a month
ptnwdapv	profile total number of weekday approvals in a month
ptnwdeve	profile total number of weekday evening approvals in a month
ptnwdmor	profile total number of weekday morning approvals in a month
ptnwdnit	profile total number of weekday night approvals in a month
ptnweaft	profile total number of weekend afternoon approvals in a month
ptnweapv	profile total number of weekend approvals in a month
ptnweeve	profile total number of weekend evening approvals in a month
ptnwemor	profile total number of weekend morning approvals in a month
ptnwenit	profile total number of weekend night approvals in a month
pvdaybtwn	profile variance in number of days between trx's (min of 3 trx)
pvraudl	profile variance of dollars per auth access month
	MERCHANT FRAUD VARIABLES
mtotturn	Merchant Total turnover for this specific merchant
msicturn	Merchant Cumulative SIC code turnover
mctrtage	Merchant Contract age for specific merchant
maagsic	Merchant Average contract age for this SIC code
mavgnbtc	Merchant Average number of transactions in a batch
maamttrx	Merchant Average amount per transaction (average amount per authorizations)
mvaramt	Merchant Variance of amount per transaction
mavgtbtc	Merchant Average time between batches
mavgtaut	Merchant Average time between authorizations for this merchant
mratks	Merchant Ratio of keyed versus swiped transactions
mnidclac	Merchant Number of identical customer accounts
mnidcham	Merchant Number of identical charge amounts
mtrxsrc	Merchant What is the source of transaction (ATM, merchant, etc.)
mtrxtrsp	Merchant How is the transaction transported to the source (terminal, non-terminal, voice authorization)
mfloor	Merchant Floor limit
mchgbks	Merchant Charge-backs received
mrtrvs	Merchant Retrievals received (per SIC, merchant, etc.). The issuer pays for a retrieval.
macqrat	Merchant Acquirer risk managment rate (in Europe one merchant can have multiple acquires, but they dont have records about how many or who.)
mprevrsk	Merchant Previous risk management at this merchant? Yes or No
mtyprsk	Merchant Type of previous risk management (counterfeit, multiple imprint, lost/stolen/not received)
msicrat	Merchant SIC risk management rate
mpctaut	Merchant Percent of transactions authorized

Network Training: Once pre-processing is complete, the fraud-related variables are fed to the network and the network is trained. The preferred embodiment uses a modeling technique known as a "feed forward" neural network. This type of network estimates parameters which define relationships among variables using a training method. The preferred training method, well known to those skilled in the art, is called "backpropagation gradient descent optimization", although other well-known neural network training techniques may also be used.

One problem with neural networks built with conventional backpropagation methods is insufficient generalizability. Generalizability is a measure of the predictive value of a neural network. The attempt to maximize generalizability can be interpreted as choosing a network model with enough complexity so as not to underfit the data but not too much complexity so as to overfit the data. One measure of the complexity of a network is the number of hidden processing elements, so that the effort to maximize generalizability translates into a selection among models having different numbers of hidden processing elements. Unfortunately, it is often not possible to obtain all the nonlinearity required for a problem by adding hidden processing elements without introducing excess complexity. Many weights that come with the addition of each new hidden processing element may not be required or even helpful for the modeling task at hand. These excess weights tend to make the network fit the idiosyncrasies or "noise" of the data and thus fail to generalize well to new cases. This problem, known as overfitting, typically arises because of an excess of weights.

Weight decay is a method of developing a neural network that minimizes overfitting without sacrificing the predictive power of the model. This method initially provides the network with all the nonlinearity it needs by providing a large number of hidden processing elements. Subsequently, it decays all the weights to varying degrees so that only the weights that are necessary for the approximation task remain. Two central premises are employed: 1) when given two models of equivalent performance on a training data set, favor the smaller model; and 2) implement a cost function that penalizes complexity as part of the backpropagation algorithm. The network is trained by minimizing this cost function. Complexity is only justified as it expresses information contained in the data. A weight set that embodies all or almost all of the information in the data and none of the noise will maximize generalizability and performance.

The cost function is constructed by introducing a "decay term" to the usual error function used to train the network. It is designed to optimize the model so that the network captures all the important information in the training set, but does not adapt to noise or random characteristics of the training set. In view of these requirements, the cost function must take into account not only prediction error, but also the significance of model weights. A combination of these two terms yields an objective function which, when minimized, generalizes optimally. Performing a conventional gradient descent with this objective function optimizes the model.

In introducing the decay term, an assumption is made about what constitutes information. The goal is to choose a decay term that accurately hypothesizes the prior distribution of the weights. In finding a good prior distribution, one examines the likelihood that the weights will have a given distribution without knowledge of the data.

Weigend et al, "Generalization by Weight-Elimination with Application to Forecasting", in *Advances in Neural Information Processing Systems* 3, pp. 875–82, and incorporated herein by reference, discloses the following cost function for weight decay:

$$\frac{1}{2}\sum_{k\epsilon D}(\text{target}_k-\text{output}_k)^2+\lambda\sum_{i\epsilon W}\frac{\omega_i^2/\omega_o^2}{1+\omega_i^2/\omega_o^2}\qquad\text{(Eq. 1)}$$

where:

D is the data set;

target_k is the target, or desired, value for element k of the data set;

output_k is the network output for element k of the data set;

λ represents the relative importance of the complexity term;

W is the weight set;

ω_i is the value of weight i; and

ω_o is a constant that controls the shape of the curve that penalizes the weights.

The first term of the Weigend function measures the performance of the network, while the second term measures the complexity of the network in terms of its size. With this

cost function, small weights decay rapidly, while large weights decay slowly or not at all.

A major failing of the Weigend cost function, and similar weight decay schemes, is that they do not accurately mimic the intended prior distribution. Finding a good prior distribution (or "prior") is a key element to developing an effective model. Most of the priors in the literature are sufficient to demonstrate the concept of weight decay but lack the strengths required to accommodate a wide range of problems. This occurs because the priors tend to decay weights evenly for a given processing element, without sufficiently distinguishing important weights (which contain more information) from unimportant weights (which contain less information). This often results either in 1) undesired decaying of important weights, which diminishes the power of the system to accommodate nonlinearity, or 2) undesired retention of excess unimportant weights, which leads to overfitting.

The present invention uses the following improved cost function, which addresses the above problems:

$$\frac{1}{2}\sum_{k\epsilon D}(\text{target}_k-\text{output}_k)^2+g\lambda\sum_{i\epsilon W}\left(c_1\omega_i^2-\frac{1}{1+|\omega_i|}\right)\qquad\text{(Eq. 2)}$$

where g represents a new term known as the interlayer gain multiplier for the decay rate, and c_1 is a constant. The interlayer gain multiplier takes into account the relative proximity of the weights to the input and output ends of the network. Thus, the interlayer gain multiplier allows application of the decay term with greater potency to elements that are closer to the inputs, where the majority of the weights typically reside, while avoiding excessive decay on weights corresponding to elements closer to the outputs, which are more critical, since their elimination can effectively sever large numbers of input-side weights.

By intensifying decay on input-side elements, the cost function of Equation 2 improves the ability of model development component **801** to decay individual weights while preserving processing elements containing valuable information. The result is that weak interactions are eliminated while valid interactions are retained. By retaining as many processing elements as possible, the model does not lose the power to model nonlinearities, yet the overfitting problem is reduced because unnecessary individual weights are removed.

Once the cost function has been iteratively applied to the network, weights that have been decayed to a very small number (defined as ϵ) are removed from the network. This step, known as "thresholding the net" is performed because it is often difficult to completely decay weights to zero.

Once the network has been trained using past data, the network's model definition is stored in data files. One portion of this definition, called the "CFG" file, specifies the parameters for the network's input variables, including such information as, for example, the lengths of the variables, their types, and their ranges. Referring now to FIG. **21**, there is shown a portion of a typical CFG file, specifying parameters for an ACCOUNT variable **2101** (representing a customer account number) and a PAUDYMDY variable **2102** (a profile variable representing the ratio of transaction days divided by the number of days in the month).

The file formats used to store the other model definition files for the network are shown below.

A

ASCII File Formats

The ASCII network data files (.cta, .sta, .lca, .wta) consist of tokens (non-whitespace) separated by whitespace (space, tab, newline). Whitespace is ignored except to separate tokens. Use of line breaks and tabs is encouraged for clarity, but otherwise irrelevant.

File format notation is as follows:

- * Bracketed text denotes a token.
- * Nonbracketed text denotes a literal token which must be matched exactly, including case.
- * Comments on the right are not part of the file format; they simply provide further description of the format.
- * In the comments, vertical lines denote a block which can be repeated. Nested vertical lines denote repeatable sub-blocks.

.cta Format

File format	Comments
cts	
<NetName>	
<Value>	| Repeated as needed

cts and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase (e.g., mbpn). The <Value>s are the network constants values, in the order defined within the constants structure. If a constants value is an array or structured type, each element or field must be a separate token, appearing in the proper order.

Example	Comments
cts	
mbpn	
2	InputSize
1	OutputSize
1	cHidSlabs
2	HiddenSize[0]
0	HiddenSize[1]
0	HiddenSize[2]
3	RandomSeed
1.0	InitWeightMax
0	WtsUpdateFlag
0	ConnectInputs
0	FnClass
1.0	Parm1
1.0	Parm2
−1.0	Parm3
0.0	Parm4
0.0	Parm5
1	cEntTbl
0.0	xLow
0.1	xHigh
0.2	HiddenAlpha[0]
0.0	HiddenAlpha[1]
0.0	HiddenAlpha[2]
0.1	OutputAlpha
0.9	HiddenBeta[0]
0.0	HiddenBeta[1]
0.0	HiddenBeta[2]
0.9	OutputBeta
0.0	Tolerance
0	WtsUpdateFlag
0	BatchSize
0	LinearOutput
0	ActTblFlag
1	StatsFlag
1	LearnFlag

In this example, HiddenSize, HiddenAlpha, and HiddenBeta are all arrays, so each element (0, 1, 2) has a separate token, in the order they appear in the type.

.sta Format

File format	Comments
sts	
<NetName>	
<cSlab>	
<nSlab>	| Repeated cSlab times

-continued

A

ASCII File Formats

```
<cPe>       |
<state>     || Repeated cPe times
```

sts and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase. <cSlab> is a count of the slabs which have states stored in the file. The remainder of the file consists of cSlab blocks, each describing the states of one slab. The order of the slab blocks in the file is not important. <nSlab> is the slab number, as defined in the xxx.h file. cPe is the number of states for the slab. <state> is the value of a single state. If the state type is an array or structured type, each element or field must be a separate token, appearing in the proper order. There should be cPe <state> values in the slab block.

Example	Comments
sts	
mbpn	
6	cSlab
0	nSlab—SlabInMbpn
2	cPeIn
0.0	StsIn[0]
0.0	StaIn[1]
1	nSlab—SlabTrnMbpn
1	cPeTrn
0.0	StsTrn[0]
2	nSlab—SlabHid0Mbpn
2	cPeHid0
0.0	StsHid0[0]
0.0	StsHid0[1]
5	nSlab—SlabOutMbpn
1	cPeOut
0.0	StsOut[0]
6	nSlab—SlabBiasMbpn
1	cPeBias
1.0	StsBias[0]
7	nSlab—SlabStatMbpn
3	cPeStat
0.0	StsStat[0]
0.0	StsStat[1]
0.0	StsStat[2]

.lca Format

```
File format        Comments

1cl
<NetName>
<cSlab>
<nSlab>     | Repeated cSlab times
<cPe>       |
<local>     || Repeated cPe times
```

The .lca format is just like the .sta format except that sts is replaced by 1cl. 1cl and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase. <cSlab> is a count of the slabs which have local data stored in the file. The remainder of the file consists of cSlab blocks, each describing the local data values of one slab. <nSlab> is the slab number, as defined in the xxx.h file. The order of the slab blocks in the file is not important. cPe is the number of local data values for the slab. <local> is the value of a single local data element. If the local data type is an array or structured type, each element or field must be a separate token, appearing in the proper order. There should be cPe <local> values in the slab block.

Example	Comments
1cl	
mbpn	
3	cSlab
2	nSlab—SlabHid0Mbpn
2	cPe
0.0	LclHid0[0].Error
0.0	LclHid0[0].NetInp
0.0	LclHid0[1].Error
0.0	LclHid0[1].NetInp

-continued

A

ASCII File Formats

5	nSlab—SlabOutMbpn
1	cPe
0.0	LclOut[0].Error
0.0	LclOut[0].NetInp
7	nSlab—SlabStatMbpn
3	cPe
0	LclStat[0].cIter
0.0	LclStat[0].Sum
0	LclStat[1].cIter
0.0	LclStat[1].Sum
0	LclStat[2].cIter
0.0	LclStat[2].Sum

In this example, the <local> values are all structured types, so each field (Error and NetInp; cIter and Sum) has a separate token, in the oder they appear in the type.

.wta Format

File format	Comments
wts	
<NetName>	
<cClass>	
<nSlab>	| Repeated cClass times
<nClass>	|
<cIcn>	|
<weight>	| | Repeated cIcn times

wts and <NetName> must appear first. <NetName> is the standard abbreviation, lowercase. <cClass> is a count of the slab/class combinations which have weight stored in the file. The remainder of the file consists of cClass blocks, each describing the weights of one slab. The order of the class blocks in the file is not important. <nSlab> is the slab number, as defined in the xxx.h file. <nClass> is the class number, as defined in the xxx.h file. <weight> is the value of a single weight. If the weight type is an array or structured type, each element or field must be a separate token, appearing in the proper order. There should be cIcn <weight> values in the slab block.

Example	Comments
wts	
mbpn	
2	cClass
2	nSlab—SlabHid0Mbpn
0	nClass—PeHid0MbpnFromPrev
6	cIcn
0.0	WtsHid0[PE_0][0]
0.0	WtsHid0[PE_0][1]
0.0	WtsHid0[PE_0][2]
0.0	WtsHid0[PE_1][0]
0.0	WtsHid0[PE_1][1]
0.0	WtsHid0[PE_1][2]
5	nSlab—SlabOutMbpn
0	nClass—PeOutMbnpnFromPrev
3	cIcn
0.0	WtsOut[PE_0][0]
0.0	WtsOut[PE_0][1]
0.0	WtsOut[PE_0][2]

Weights values for a slab and class are stored as a one-dimensional array, but conceptually are indexed by two values—PE and interconnect within PE. The values are stored in row-major order, as exemplified here.

Transaction Processing Component **802**

Once the model has been created, trained, and stored, fraud detection may begin. Transaction processing component **802** of system **100** preferably runs within the context of a conventional authorization or posting system for customer transactions. Transaction processing component **802** reads current transaction data and customer data from databases **805**, **806**, and generates as output fraud scores representing the likelihood of fraud for each transaction. Furthermore, transaction processing component **802** can compare the likelihood of fraud with a predetermined threshold value, and flag transactions for which the threshold is exceeded.

The current transaction data from database **805** typically includes information such as: transaction dollar amount; date; time (and time zone if necessary); approve/decline code; cash/merchandise code; available credit (or balance);

credit line; merchant category code; merchant ZIP code; and PIN verification (if applicable).

The customer data from database **806** typically includes information from three sources: 1) general information on the customer; 2) data on all approved or declined transactions in the previous seven days; and 3) a profile record which contains data describing the customer's transactional pattern over the last six months. The general information on the customer typically includes information such as: customer ZIP code; account open date; and expiration date. The profile record is a single record in a profile database summarizing the customer's transactional pattern in terms of moving averages. The profile record is updated periodically (usually monthly) with all of the transactions from the period for the customer, as described below.

System **100** can operate as either a batch, semi-real-time, or real-time system. The structure and processing flow of each of these variations will now be described.

Batch System: FIG. **14** shows operation of a batch system. Transactions are recorded throughout the day or other convenient period **1402**. At the end of the day, the system performs steps **1403** to **1409** for each transaction. It obtains data describing the current transaction **1403**, as well as past transaction data, customer data, and profile data **1404**. It then applies this data to the neural network **1405** and obtains a fraud score **1406**. If the fraud score exceeds a threshold **1407**, the account is flagged **1408**. In the batch system, therefore, the transaction which yielded the high fraud score cannot itself be blocked; rather, the account is flagged **1404** at the end of the day so that no future transactions are possible. Although the batch system does not permit immediate detection of fraudulent transactions, response-time constraints may mandate use of the batch system in some implementations.

Semi-Real-Time System: The semi-real-time system operates in a similar manner to the batch system and uses the same data files, but it ensures that no more than one high-scoring transaction is authorized before flagging the account. In this system, as shown in FIG. **15**, fraud likelihood determination is performed (steps **1504** to **1509**) immediately after the transaction is authorized **1503**. Steps **1504** to **1509** correspond to steps **1403** to **1409** of the batch system illustrated in FIG. **14**. If the likelihood of fraud is high, the account is flagged **1509** so that no future transactions are possible. Thus, as in the batch system, the current transaction cannot be blocked; however, the semi-real-time system allows subsequent transactions to be blocked.

Real-Time System: The real-time system performs fraud likelihood determination before a transaction is authorized. Because of response-time constraints, it is preferable to minimize the number of database access calls when using the real-time system. Thus, in this embodiment, all of the customer information, including general information and past transaction data, is found in a single record of profile database **806**. Profile database **806** is generated from past transaction and customer data before the transaction processing component starts operating, and is updated after each transaction, as described below. Because all needed data are located in one place, the system is able to retrieve the data more quickly than in the batch or semi-real-time schemes. In order to keep the profile database **806** current, profile records are updated, using moving averages where applicable, after each transaction.

Referring now to FIG. **16**, there is shown a flowchart of a real-time system using the profile database. Upon receiving a merchant's request for authorization on a transaction **1602**, the system obtains data for the current transaction **1603**, as well as profile data summarizing transactional patterns for the customer **1604**. It then applies this data to the stored neural network model **1605**. A fraud score (representing the likelihood of fraud for the transaction) is obtained **1606** and compared to a threshold value **1607**. Steps **1601** through **1607** occur before a transaction is authorized, so that the fraud score can be sent to an authorization system **1608** and the transaction blocked by the authorization system if the threshold has been exceeded. If the threshold is not exceeded, the low fraud score is sent to the authorization system **1609**. The system then updates customer profile database **806** with the new transaction data **1610**. Thus, in this system, profile database **806** is always up to date (unlike the batch and semi-real-time systems, in which profile database **806** is updated only periodically).

Referring now to FIG. **12**, there is shown the method of creating a profile record. The system performs the steps of this method when there is no existing profile record for the customer. The system reads the past transaction database **1101** for the past six months and the customer database **1103** (steps **1202** and **1203** respectively). It generates a new profile record **1204** with the obtained data and saves it in the profile database **1205**. If there are more accounts to be processed **1206**, it repeats steps **1202** through **1205**.

Referring now to FIG. **13**, there is shown the method of updating an existing profile record. The system reads the past transaction database **1101** for the past six months, customer database **1103** and profile database (steps **1302**, **1303**, and **1304** respectively). It combines the data into a single value for each variable in the profile database. This value is generated using one of two formulas.

For variables that represent average values over a period of time (for example, mean dollars of transactions in a month), Equation 3 is used:

$$\text{newProfData}=((1-\alpha)*\text{oldProfData})+(\alpha*\text{currentVal})) \qquad \text{(Eq.3)}$$

For variables that represent extreme values over a period of time (for example, highest monthly balance), Equation 4 is used:

$$\text{newProfData}=\max(\text{currentVal},\beta*\text{oldProfData}) \qquad \text{(Eq.4)}$$

In Equations 3 and 4:

newProfData is the new value for the profile variable;

oldProfData is the old value for the profile variable;

currentVal is the most recent value of the variable, from the past transaction database; and

α and β are decay factors which are used to give more importance to recent months and less importance to months further in the past.

The value of β is set so that older data will "decay" at an acceptable rate. A typical value for β is 0.95.

The value of α is generated as follows: For the batch and semi-realtime systems, α is set to a value such that the contribution of the value from more than six months previous is nearly zero. For profiles that have been in existence for at least six months, the value of α is $1/6$. For newer profiles, the value is 1/(n+1), where n is the number of months since the profile was created. For the real-time system, profile updates do not occur at regular intervals. Therefore, α is determined using the following equation:

$$\alpha=1-\exp(-t/T) \qquad \text{(Eq.5)}$$

where:

t is the time between the current transaction and the last transaction; and

T is a time constant for the specific variable.

Furthermore, for the real-time system, currentVal represents the value of the variable estimated solely using information related to the current transaction and the time since the last transaction, without reference to any other historical information.

Once the new values for the profile variables have been generated, they are placed in an updated profile record **1305** and saved in the profile database **1306**. If there are more accounts to be processed **1307**, the system repeats steps **1302** through **1306**.

In all of these embodiments, the current transaction data and the customer data are preferably pre-processed to derive fraud-related variables which have been empirically determined to be effective predictors of fraud. This is done using the same technique and the same fraud-related variables as described above in connection with neural network training.

Referring now to FIGS. **17** through **19**, there are shown flowcharts illustrating the operation of the preferred embodiment of the transaction processing component. Some of the individual elements of the flowchart are indicated by designations which correspond to module names. The following brief description summarizes the processing.

Referring now to FIG. **17**, there is shown the overall operation of transaction processing component **802**. First the system runs module CINIT-NET **1702**, which initializes network structures. Then, it runs module CSCORE **1703**. Module CSCORE **1703** uses current transaction data, data describing transactions over the past seven days, a profile record, and customer data to generate a fraud score indicating the likelihood that the current transaction is fraudulent, as well as reason codes (described below). The system then checks to see whether there are more transactions to be processed **1704**, and repeats module CSCORE **1703** for any additional transactions. When there are no more to be processed, the system runs module FREENET **1705**, which frees the network structures to allow them to be used for further processing.

Referring now to FIG. **18**, there is shown the operation of module CSCORE **1703**. First, module CSCORE **1703** obtains current transaction data, data describing transactions of the past seven days, the profile record, and customer data (steps **1802** through **1805**). From these data, module CSCORE **1703** generates the fraud-related variables **1806** described above. Then, it runs module DeployNet **1807**, which applies the fraud-related variables to the stored neural network and provides a fraud score and reason codes. CSCORE then outputs the score and reason codes **1808**.

Referring now to FIG. **19**, there is shown the operation of module DeployNet **1807**. Module DeployNet **1807** first scales the fraud-related variables **1902** to match the scaling previously performed in model development. If the value of a variable is missing, DeployNet sets the value to equal the mean value found in the training set. Then it applies the scaled variables to the input layer of neural network **108**, in step **1903**. In step **1904**, it processes the applied data through the network to generate the fraud score. The method of iterating the network is well known in the art.

In addition to providing fraud scores, in step **1904**, module DeployNet **1807** optionally generates "reason codes". These codes indicate which inputs to the model are most important in determining the fraud score for a given transaction. Any technique that can track such reasons may be used. In the preferred embodiment, the technique set forth in co-pending U.S. application Ser. No. 07/814,179, (attorney's docket number 726) for "Neural Network Having Expert System Functionality", by Curt A. Levey, filed Dec. 30, 1991, the disclosure of which is hereby incorporated by reference, is used.

The following module descriptions summarize the functions performed by the individual modules.

FALCON C FILES

FILE NAME: CINITNET
DESCRIPTION: Contains code to allocate and initialize the network structures.
    FUNCTION NAME: CINITNET( )
    DESCRIPTION: Allocate and initialize the network structures.
FILE NAME: CSCORE
DESCRIPTION: Generates fraud related variables and iterates the neural network.
    FUNCTION NAME: SCORE( )
    DESCRIPTION: Creates fraud related variables from raw variables and make calls to initialize the input layer and iterate the neural network.
    FUNCTION NAME: setInput( )
    DESCRIPTION: Sets the input value for a processing element in the input layer.
    FUNCTION NAME: hiReason( )
    DESCRIPTION: Finds the three highest reasons for the score.
FILE NAME: CFREENET
DESCRIPTION: Makes function calls to free the network structures.
    FUNCTION NAME: CFREENET( )
    DESCRIPTION: Frees the network structures.
FILE NAME: CCREATEP
DESCRIPTION: Contains the cardholder profile creation code.
    FUNCTION NAME: createpf( )
    DESCRIPTION: Creates a profile record for a cardholder using the previous month's authorizations and cardholder data.
FILE NAME: CUPDATEP
DESCRIPTION: Updates a profile of individual cardholder activity.
    FUNCTION NAME: updatepf( ):
    DESCRIPTION: Updates a profile record for a cardholder using the previous profile record values as well as the previous month's authorizations and cardholder data
FILE NAME: CCOMMON
DESCRIPTION: This file contains functions which are needed by at least two of the

-continued

FALCON C FILES

following; creatpf( ), updatepf( ), score( ).
FUNCTION NAME: accumMiscCnts( )
DESCRIPTION: Increments counters of various types for each
authorization found.
FUNCTION NAME: accumSicCnts( )
DESCRIPTION: Increments SIC variable counters.
FUNCTION NAME: initSicCounts( )
DESCRIPTION: Initializes the SIC variable counters.
FUNCTION NAME: updateSicMovAvgs( )
DESCRIPTION: Updates the SIC profile variables.
FUNCTION NAME: writeMiscToProfile( )
DESCRIPTION: Writes various variables to the profile record
after they have been calculated.
FUNCTION NAME: hncDate( )
DESCRIPTION: Converts a Julian date to a date indicating
the number of days since Jan 1, 1990.
FUNCTION NAME: missStr( )
DESCRIPTION: Checks for "missing" flag (a period) in a null
terminated string. String must have only blanks
and a period to qualify as missing. A string with
only blanks will also qualify as "missing".

Cascaded Operation

One way to improve system performance is via "cascaded" operation. In cascaded operation, more than one neural network model is used. The second neural network model is trained by model development component **801** in a similar manner to that described earlier. However, in training the second model, model development component **801** uses only those transactions that have fraud scores, as determined by prior application to the first neural network model, above a predetermined cascade threshold. Thus, the second model provides more accurate scores for high-scoring transactions. While the same fraud-related variables are available to train both models, it is often the case that different variables are found to be significant in the two models.

Referring now to FIG. **20**, there is shown a flowchart of the operation of the transaction processing component in a cascaded system. First, transaction processing component **802** scores each transaction using the first model **2002**, as described above. Those transactions that score above the cascade threshold **2003** are applied to the second neural network model **2005**. The system outputs scores and reason codes from either the first model **2004** or the second model **2006**, as appropriate.

The above-described cascading technique may be extended to include three or more neural network models, each having a corresponding cascade threshold.

Performance Monitor

The system periodically monitors its performance by measuring a performance metric comprising the fraud detection rate and the false positive rate. Other factors and statistics may also be incorporated into the performance metric. When the performance metric falls below a predetermined performance level, the system may either inform the user that the fraud model needs to be redeveloped, or it may proceed with model redevelopment automatically.

From the above description, it will be apparent that the invention disclosed herein provides a novel and advantageous method of detecting fraudulent use of customer accounts and account numbers, which achieves high detection rates while keeping false positive rates relatively low. The foregoing discussion discloses and describes merely exemplary methods and embodiments of the present invention. As will be understood by those familiar with the art, the invention may be embodied in many other specific forms without departing from the spirit or essential characteristics thereof. For example, other predictive modeling techniques besides neural networks might be used. In addition, other variables might be used in both the model development and transaction processing components.

Accordingly, the disclosure of the present invention is intended to be illustrative of the preferred embodiments and is not meant to limit the scope of the invention. The scope of the invention is to be limited only by the following claims.

What is claimed is:

1. In a computer having a processor and storage, a computer-implemented process for detecting a fraudulent transaction in a customer account, comprising the steps of:

obtaining past transaction data for processing by the computer

pre-processing the past transaction data to derive past fraud related variables;

generating a predictive model with the processor from the past fraud related variables;

storing a representation of the predictive model in the computer storage;

receiving current transaction data for processing by the processor;

receiving customer data for processing by the processor; and

generating a computer signal indicative of the likelihood of fraud in the current transaction, wherein the processor generates the computer signal by applying the current transaction data and the customer data to the stored predictive model.

2. The computer-implemented process of claim **1**, wherein the step of obtaining customer data comprises accessing a computer database containing general customer data and a computer database containing customer transactional pattern data.

3. The computer-implemented process of claim **1**, wherein the step of obtaining customer data comprises accessing no more than one profile computer database record containing customer transactional pattern data.

4. The computer-implemented process of claim **3**, wherein the profile computer database record further contains general customer data.

5. The computer-implemented process of claim **1**, wherein the current transaction data and the customer data each comprise a plurality of elements and the computer processes each element by:

determining a relative contribution of the element to the determined likelihood of fraud;

determining from each relative contribution thus determined a reason code value; and

generating a computer signal indicative of the reason code value.

6. The computer-implemented process of claim **1**, further comprising the steps of:

comparing the computer signal indicative of the likelihood of fraud with a preset threshold value; and

responsive to the computer signal exceeding the preset threshold value, generating a computer signal indicating fraud.

7. The computer-implemented process of claim **1**, further comprising the iterative steps of:

determining a cascade threshold value;

comparing the computer signal indicative of the likelihood of fraud with the cascade threshold value; and

responsive to the computer signal exceeding the cascade threshold value, generating another computer signal indicative of the likelihood of fraud in the current transaction by applying the current transaction data and the customer data to another predictive model.

8. The computer-implemented process of claim **1**, further comprising the steps of:

monitoring a performance metric of the computer generated predictive model, wherein the processor monitors the performance metric;

comparing the performance metric with a predetermined performance level; and

generating and storing a new predictive model from past transaction data responsive to the performance level exceeding the performance metric, wherein the new predictive model is generated by the processor and stored in the computer storage.

9. the computer-implemented process of claim **8**, wherein the performance metric comprises:

a fraud detection rate measurement; and

a false positive rate measurement.

10. The computer-implemented process of claim **1**, further comprising the steps of:

pre-processing the current transaction data to derive current fraud-related variables; and

pre-processing the customer data to derive customer fraud-related variables;

wherein the computer signal representing the likelihood of fraud is generated responsive to application of the current fraud-related variables and the customer fraud-related variables to the stored predictive model.

11. The computer-implemented process of claim **10**, wherein the past fraud-related variables and the current fraud-related variables each comprise at least:

factors obtained from data referring to transaction dollar amounts related to fraud;

factors obtained from data referring to transaction dates and times related to fraud;

factors obtained from data referring to transaction approvals and declines related to fraud; and

factors obtained from data referring to risk groups related to fraud.

12. The computer-implemented process of claim **10**, wherein the past fraud-related variables and the current fraud-related variables each comprise at least:

factors obtained from data referring to customers related to fraud; and

factors obtained from data referring to merchants related to fraud.

13. The computer-implemented process of claim **10**, further comprising the steps of, for each variable in the set of derived current fraud-related variables and derived customer fraud-related variables:

determining a relative contribution of the variable to the determined likelihood of fraud;

determining from each relative contribution thus determined a reason code value; and

generating a computer signal indicative of the reason code value.

14. A computer-implemented process for detecting fraud for a transaction on a customer account, comprising the steps of:

obtaining past transaction data for processing by the computer;

pre-processing the past transaction data to derive past fraud-related variables;

training a neural network on the computer with the derived past fraud-related variables;

storing the neural network in storage associated with the computer;

obtaining current transaction data for processing by the computer;

pre-processing the current transaction data to derive current fraud-related variables;

obtaining customer data for processing by the computer;

pre-processing the customer data to derive customer fraud-related variables; and

generating a computer signal representing the likelihood of fraud responsive to application of the current fraud-related variables and the customer fraud-related variables to the stored neural network.

15. In a computer having a processor and storage, a computer-implemented process of training a neural network, the neural network for predicting fraudulent transactions in a customer account based on selected data, the neural network being represented on the computer and stored in the computer storage and comprising a plurality of interconnected processing elements, each processing element comprising:

a plurality of inputs;

a plurality of weights, wherein each weight is associated with a corresponding input by the processor to generate weighted inputs;

means for combining the weighted inputs; and

a transfer function for processing the combined weighted inputs on the processor to produce an output;

the training process comprising the iterative steps of:

applying input data to the neural network to generate output data, wherein the processor applies the input data to the neural network and generates the output data;

comparing the generated output data to a desired output, wherein the processor performs the comparison;

adjusting operation of the neural network responsive to the results of the comparing step; and

after the iterative steps of applying, comparing, and adjusting, storing the neural network in the computer storage.

16. The computer-implemented process of claim **15**, wherein the step of adjusting operation of the neural network comprises the substeps of:

selecting a subset of the weights to be decayed; and

decaying the selected subset of weights.

17. The computer-implemented process of claim **16**, wherein the substep of selecting a subset of the weights to be decayed comprises applying and minimizing a cost function including an interlayer gain multiplier which varies a decay rate responsive to the location of a weight within the network.

18. The computer-implemented process of claim **17**, wherein the cost function is of the form:

$$\frac{1}{2}\sum_{k \in D}(\text{target}_k - \text{output}_k)^2 + g\lambda \sum_{i \in W}\left(c_1\omega_i^2 - \frac{1}{1+|\omega_i|}\right),$$

wherein:

D represents a data set;

target_k represents a target value for element k of the data set;

output_k represents a network output for element k of the data set;

g represents the interlayer gain multiplier;

λ represents the relative importance of the complexity term;

W represents a weight set;

ω_i represents a value of weight i; and

c_1 represents a constant.

19. A system for detecting a fraudulent transaction in a customer account, comprising:

a computer processor for executing programmed instructions and for storing and retrieving data;

program memory, coupled to the processor, for storing program instruction steps for execution by the processor;

a predictive model component, coupled to the processor, for determining the likelihood of a fraudulent transaction;

past transaction data storage, coupled to the processor, for receiving, storing, and sending past transaction data;

a model development component, coupled to the processor, for training the predictive model based on the past transaction data in accordance with program instructions in the program memory and executed by the processor, thereby generating a trained predictive model;

current transaction data storage, coupled to the processor, for receiving, storing, and sending current transaction data;

customer data storage, coupled to the processor, for receiving, storing, and sending customer data; and

an output device, coupled to the processor, for outputting a computer signal indicative of the likelihood of fraud in a transaction, wherein the processor generates the computer signal in accordance with program instructions in the program memory and executed by the processor, said computer signal being responsive to the application of the current transaction data and the customer data to the trained predictive model.

20. The system of claim **19**, wherein the model development component derives past fraud-related variables as a function of the past transaction data, and said past fraud-related variables are used to train the predictive model.

21. The system of claim **19**, wherein:

the predictive model component comprises a neural network, coupled to the processor; and

the model development component trains the neural network based on the past transaction data in accordance with program instructions in the program memory and executed by the processor, thereby generating a trained neural network;

wherein the processor generates the computer signal by applying the current transaction data and the customer data to the trained neural network.

22. The system of claim **19**, further comprising:

a past transaction data pre-processor, coupled to the processor, for deriving past fraud-related variables from the past transaction data;

wherein the model development component trains the predictive model based on the past fraud-related variables in accordance with program instructions in the program memory and executed by the processor, thereby generating the trained predictive model;

a current transaction data pre-processor, coupled to the processor, for deriving current fraud-related variables from the current transaction data; and

a customer data pre-processor, coupled to the processor, for deriving customer fraud-related variables from the customer data;

wherein the processor generates the computer signal by applying the current fraud-related variables and the customer fraud-related variables to the trained predictive model.

23. In a system for detecting fraud in a transaction on an account belonging to a customer, the system including a computer processor for executing programmed instructions and for storing and retrieving data, a computer readable memory storing thereon:

a neural network, coupled to the processor, for determining the likelihood of a fraudulent transaction;

past transaction data storage, coupled to the processor, for receiving, storing, and sending past transaction data;

a past transaction data pre-processor, coupled to the processor, for deriving past fraud-related variables from the past transaction data;

a model development component, coupled to the processor, for training the neural network based on the past fraud-related variables, thereby generating a trained neural network;

current transaction data storage, coupled to the processor, for receiving, storing, and sending current transaction data;

a current transaction data pre-processor, coupled to the processor, for deriving current fraud-related variables from the current transaction data;

customer data storage, coupled to the processor, for receiving, storing, and sending customer data; and

a customer data pre-processor, coupled to the processor, for deriving customer fraud-related variables from the customer data;

wherein the processor generates a computer signal indicative of the likelihood of fraud in a transaction, said computer signal being responsive to the application of the current fraud-related variables and the customer fraud-related variables to the trained neural network.

24. In a computer-controlled transaction processing system including predictive modeling means for receiving current transaction data, processing the current transaction data, and outputting a plurality of output values, including a score value representing a likelihood of a fraudulent transaction, an improved computer-implemented process for identifying and determining fraudulent transaction data, comprising the steps of:

prior to receiving the current transaction data for at least one current transaction;

generating a consumer profile for each of a plurality of consumers from a plurality of past fraud-related variables and from consumer data, each consumer profile describing historical spending patterns of a corresponding consumer, the past fraud-related variables being derived by pre-processing past transaction data, the past transaction data including values for a plurality of transaction variables for a plurality of past transactions, the consumer data including values for each consumer for a plurality of consumer variables;

training the predictive modeling means with the consumer profiles and with the past fraud-related variables to obtain a predictive model; and

storing the obtained predictive model in the computer; receiving current transaction data for a current transaction of a consumer;

receiving consumer data associated with the consumer;

receiving the consumer profile associated with the consumer;

pre-processing the obtained current transaction data, consumer data, and consumer profile to derive current fraud-related variables for the current transaction;

determining the likelihood of fraud in the current transaction by applying the current fraud-related variables to the predictive model; and

outputting from the predictive modeling means an output signal indicating the likelihood that the current transaction is fraudulent.

25. The computer-implemented process of claim **24**, wherein the generating step comprises the substeps of:

receiving past transaction data for a plurality of past transactions, the past transaction data providing values for a plurality of transaction variables;

receiving consumer data for each of a plurality of consumers, the consumer data providing values for a plurality of consumer variables for each consumer;

pre-processing the past transaction data to derive past fraud-related variables wherein at least some of the past fraud-related variables are not present in the plurality of variables in the past transaction data; and

generating a consumer profile for each consumer from the past fraud-related variables and the received consumer data, each consumer profile describing historical spending patterns of the consumer.

26. The computer-implemented process of claim **24**, further comprising the step of updating the received consumer profile with the received current transaction data.

27. The computer-implemented process of claim **24**, wherein the step of training the predictive modeling means comprises the substeps of:

applying the consumer profile and the derived past fraud-related variables to the predictive modeling means;

ranking output data from the predictive modeling means as a function of a quality measurement;

adjusting the predictive modeling means as a function of the ranking step; and

repeating the applying, ranking, and adjusting steps until the quality measurement exceeds a predetermined level indicating that the predictive modeling means is adequately trained.

28. The computer-implemented process of claim **27**, wherein the step of training the neural network comprises the substeps of:

applying the consumer profile and the derived past fraud-related variables to the neural network;

ranking output data from the neural network as a function of a quality measurement;

adjusting the neural network as a function of the ranking step; and

repeating the applying, ranking, and adjusting steps until the quality measurement exceeds a predetermined level indicating that the neural network is adequately trained.

29. The computer-implemented process of claim **24**, wherein the step of training the predictive modeling means comprises training a neural network organized as a plurality of input processing elements for receiving the plurality of data values in the transaction data, a plurality of hidden processing elements coupled to the input processing elements for processing the transaction data, and a plurality of output processing elements coupled to the hidden processing elements for outputting the plurality of output values.

30. The computer-implemented process of claim **29**, wherein the neural network comprises a plurality of processing elements linked by connections characterized by weights, and the step of adjusting the predictive model comprises the steps of:

selecting a subset of the weights to be decayed; and

decaying the selected subset of weights.

31. The computer-implemented process of claim **30**, wherein the substep of selecting a subset of the weights to be decayed comprises applying and minimizing a cost function including an interlayer gain multiplier which varies a decay rate responsive to the location of a weight within the network.

32. The computer-implemented process of claim **31**, wherein the cost function is of the form:

$$\frac{1}{2}\sum_{k\epsilon D}(\text{target}_k-\text{output}_k)^2+g\lambda\sum_{i\epsilon W}\left(c_1\omega_i^2-\frac{1}{1+|\omega_i|}\right),$$

wherein:

D represents a data set;

target_k represents a target value for element k of the data set;

output_k represents a network output for element k of the data set;

g represents the interlayer gain multiplier;

l represents the relative importance of the complexity term;

W represents a weight set;

w_i represents a value of weight i; and

c_1 represents a constant.

33. The computer-implemented process of claim **24**, wherein the current transaction data, the consumer profile, and the consumer data each comprise a plurality of data elements, further comprising the steps of, for at least one of the data elements:

determining a relative contribution value of the data element to the output signal indicating the likelihood that the current transaction is fraudulent;

determining a reason code as a function of the relative contribution value;

retrieving an explanation associated with the determined reason code value; and

outputting a computer signal indicative of the reason code and the explanation.

34. The computer-implemented process of claim **24**, further comprising the steps of:

monitoring a performance metric of the predictive modeling means, the performance metric comprising at least one of a fraud detection rate measurement and a false positive rate measurement;

comparing the performance metric with a predetermined performance level for the performance metric; and

responsive to the predetermined performance level exceeding the performance metric, repeating the step of training the predictive modeling means.

35. The computer-implemented process of claim **24**, wherein the past fraud-related variables and the current fraud-related variables each comprise at least:

transaction dollar amounts of past transactions;

transaction dates and times of past transactions;

transaction approvals and declines of past transactions;

risk groups of past transactions; and

merchants of past transactions.

36. In a computer system comprising:

a computer-readable memory; and

a neural network stored in the computer readable memory, the neural network comprising a plurality of interconnected processing elements, each processing element being in a layer of the neural network, each layer having a distance to an input layer, each processing element comprising:

a plurality of inputs (x);

a plurality of weights (w), each weight w associated with a corresponding input (x) to form weighted inputs;

a summation function for combining the weighted inputs; and,

a transfer function for processing the combined weighted inputs into an output (z);

an improved computer-implemented process for training the neural network characterized by:

iteratively decaying the weights of at least one processing element by a cost function that varies a decay rate for decaying the weights by a function of the distance of the input layer from the layer containing the processing element.

37. The computer-implemented process of claim **36**, wherein the cost function is of the form:

$$\frac{1}{2}\sum_{k\epsilon D}(\mathrm{target}_k-\mathrm{output}_k)^2+g\lambda\sum_{i\epsilon W}\left(c_1\omega_i^2-\frac{1}{1+|\omega_i|}\right)$$

wherein:

D represents a data set;

target_k represents a target value for an element k of the data set;

output_k represents a neural network output for element k of the data set;

g represents an interlayer gain multiplier that varies as a function of the distance between the input layer and the layer containing the processing element;

l represents the relative importance of the decay rate term;

W represents a weight set;

w_i represents a value of weight i; and

c_1 represents a constant.

38. In a computer-controlled transaction processing system including predictive modeling means for receiving current transaction data, processing the current transaction data, and outputting a plurality of output values, including a score value representing a likelihood of a fraudulent transaction, an improvement for identifying and determining fraudulent transaction data, comprising:

a model development component for developing a predictive model, comprising:

means for receiving past transaction data for a plurality of past transactions, the past transaction data providing values for a plurality of transaction variables;

means for receiving consumer data for each of a plurality of consumers, the consumer data providing values for a plurality of consumer variables for each consumer;

means for pre-processing the past transaction data to derive past fraud-related variables wherein at least some of the past fraud-related variables are not present in the plurality of variables in the past transaction data;

means for generating a consumer profile for each individual consumer, from the past fraud-related variables and the received consumer data, the consumer profile describing historical spending patterns of the consumer;

means for training the predictive model with the consumer profiles and with the past fraud-related variables; and

means for storing the trained predictive model in the computer; and

a model application component, for applying the trained predictive model, comprising:

means for receiving current transaction date for a transaction of a consumer;

means for receiving consumer data associated with the consumer;

means for receiving the consumer profile associated with the consumer;

a current transaction data pre-processor, for pre-processing the obtained current transaction data, consumer data, and consumer profile to derive current fraud-related variables for the current transaction;

means for determining the likelihood of fraud in the current transaction by applying the current fraud-related variables to the predictive model; and

means for outputting from the predictive model an output signal indicating the likelihood that the current transaction is fraudulent.

* * * * *

UNITED STATES PATENT AND TRADEMARK OFFICE

CERTIFICATE OF CORRECTION

Page 1 of 3

PATENT NO.	: 5,819,226
DATED	: October 6, 1998
INVENTOR(S)	: Krishna M. Gopinathan, et. al.

It is certified that error appears in the above-identified patent and that said Letters Patent is hereby corrected as shown below:

The Title page should be deleted and substitute therefor the attached title page.

US005819226A Page 2 of 3

United States Patent [19]

Gopinathan et al.

[11] **Patent Number:** 5,819,226

[45] **Date of Patent:** Oct. 6, 1998

[54] **FRAUD DETECTION USING PREDICTIVE MODELING**

[75] Inventors: **Krishna M. Gopinathan**; **Louis S. Biafore**; **William M. Ferguson**; **Michael A. Lazarus**, all of San Diego; **Anu K. Pathria**, Oakland; **Allen Jost**, San Diego, all of Calif.

[73] Assignee: **HNC Software Inc.**, San Diego, Calif.

[21] Appl. No.: **941,971**

[22] Filed: **Sep. 8, 1992**

[51] **Int. Cl.**^{6} **G06F 157/00**

[52] **U.S. Cl.** **705/1**

[58] **Field of Search** 364/401, 406, 364/408; 395/21, 23; 235/23, 380; 705/35, 1

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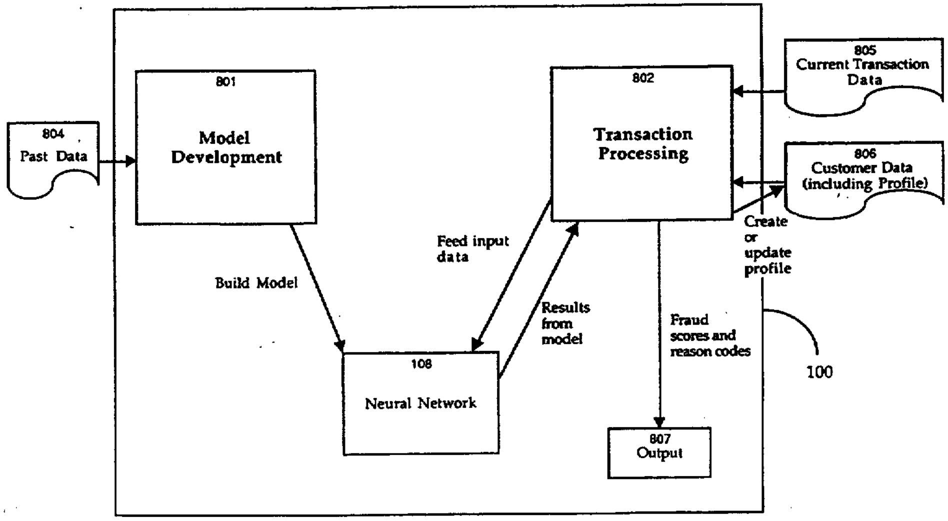
Primary Examiner—Gail O. Hayes

Attorney, Agent, or Firm—Fenwick & West LLP

[57] **ABSTRACT**

An automated system and method detects fraudulent transactions using a predictive model such as a neural network to evaluate individual customer accounts and identify potentially fraudulent transactions based on learned relationships among known variables. The system may also output reason codes indicating relative contributions of various variables to a particular result. The system periodically monitors its performance and redevelops the model when performance drops below a predetermined level.

38 Claims, 21 Drawing Sheets



UNITED STATES PATENT AND TRADEMARK OFFICE

CERTIFICATE OF CORRECTION

Page 3 of 3

PATENT NO.: 5,819,226

ISSUED: October 6, 1998

INVENTOR(S): Krishna M. Gopinathan, Louis S. Biafore, William M. Ferguson, Michael A. Lazarus, Anu K. Pathria, and Allen Jost

It is certified that error appears in the above-identified patent and that said Letters Patent is hereby corrected as shown below:

Figure 8, Box 805, replace "Property Data" with --Current Transaction Data--.

Figure 8, Box 806, replace "Area Data" with --Customer Data (including Profile)--.

Column 35, line 61, replace "said computer signal being responsive to the application of" with --by applying--.

Column 38, line 54, replace "1" with --λ--.

Column 40, line 4, replace "1" with --λ--.

Column 40, line 43, replace "date" with -data--.

Signed and Sealed this

Second Day of May, 2000

Attest:

Q. TODD DICKINSON

Attesting Officer

Director of Patents and Trademarks